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Fall detectors for people with dementia

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Fall detectors for people with dementia

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Contents

Abstract

By far the biggest injury risk faced by people with late onset dementia is a serious fall. Commercial fall detectors are available which automatically alert a call centre or carer if they detect a fall. They use accelerometers to look for the kinematics of a fall but this method is unreliable and the frequent false alarms must be cancelled by the wearer. This is inappropriate for someone with dementia.

This thesis examines how a wrist-worn fall detector better suited to someone with dementia might be built. It reviews what other sensors could be used alongside accelerometers, and whether looking for the physiological effects of falling might be beneficial. It concludes that the pulse provides a source of data and describes three empirical trials to examine whether the body pose can be determined from the pulse waveform. A small convenience sample proved the viability of the concept, followed by a larger study to investigate it further, and finally a trial in people of the same age group as late onset dementia sufferers.

Producing a technically better device is not sufficient, as it must also be usable by the people it is intended for. The thesis describes two qualitative studies which use carers to define, and then evaluate, a conceptual fall detector suitable for people with moderate or severe dementia which fits underneath a wrist watch.

The thesis argues that wearable fall detectors should utilise physiological data to complement kinematic data. It demonstrates the practicality of a novel technique for determining body position using the pulse waveform, and finally concludes that it would be possible to build the conceptual fall detector utilising this technique.

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Chapter 1

Background

This chapter gives an overview of dementia and falling, and explains why falling is a serious problem for people with dementia. It closes with a review of fall detectors, electronic devices which can summon help if someone falls and identifies the major difficulties with them which would benefit from further research and development.

1.1 Introduction

A combination of effective public health, low-cost food and excellent health care in developed countries means that people are living longer than in earlier generations. The proportion of people in the UK who are aged 65 or over has trebled in the last century (Office for National Statistics, 2012), and the absolute numbers have increased five-fold to 10.4 million.

Similar increases have been seen across all developed countries. In 1950 just 1% of people were aged 80 or over in a list of 32 developed countries but by 2004 it had risen to 4% (Rau et al., 2008). Combined with population growth this means that the 3.1 million elderly people of 1950 are now 37 million.

This presents major challenges for health care, in particular coping with the people who suffer from those diseases which are either a direct consequence of age or are more likely to occur in older people.

A gradual reduction in bone density and muscle bulk with age makes people more fragile as they get older. A multitude of other age related deficiencies such as declining eyesight, neuromotor control, and arthritis makes them more likely to trip or fall. This means that elderly people are much more likely to be injured by falls because they are both more common and more dangerous than in younger people. Falling is the largest cause of fatal injury in people over age 75 (Masud and Morris, 2001).

Some diseases which disproportionately afflict older people cause degeneration of the brain and can result in major neurocognitive disorder, otherwise known as dementia. Although it is not an inevitable consequence of age (Wimo et al., 2010), the overwhelming majority of people who have dementia are elderly. Dementia is both a personal catastrophe for the millions of sufferers and their families, and one of the most serious public health problems of the twenty-first century. 0.5% of the world's population suffer from this devastating progressive condition (Abbott, 2011).

The rest of this chapter looks at dementia in much more detail, and then at falls in elderly people and why they are a greater risk for people with dementia. It closes with an examination of fall detection, which is one of several technologies which can help reduce the harm caused by falls.

1.2 Dementia

Dementia, or major neurocognitive disorder (MNCD), is a broadly defined syndrome characterised by progressive degeneration of brain tissue which causes a deterioration in the person's cognitive abilities (Ritchie and Lovestone, 2002). Whilst dementia can be caused by more than 60 diseases (Haase, 1977) in practice just half a dozen are responsible for the majority of cases.

The symptoms usually start with deterioration of mental functions such as memory or judgement, and gradually and inexorably worsen until the individual is incapable of performing normal tasks of daily living without help (van der Flier and Scheltens, 2005). In the final stages, the sufferer becomes unable even to recognise previously familiar people and places.

Almost all people with dementia are aged 65 or over, and are described as having *late-onset dementia*. Within Europe whilst only 0.054% people aged 30–64 have dementia, 6.4% of those aged over 65 suffer from it (van der Flier and Scheltens, 2005).

Of course people do not suddenly enter a risk zone on their 65th birthday, and at 65 0.8% of people already have symptoms and the incidence increases exponentially with age, roughly doubling with every four years (Haan and Wallace, 2004). However, dementia does not seem to be inevitable. Although studies of centenarians have been handicapped by small sample sizes, they typically find 30-60% with dementia and an additional 20-30% suffering from other cognitive problems (MacKnight, 2003).

In the UK 2.2% of people with dementia are under 65 (LSE PSSRU and the KCL Institute of Psychiatry, 2007), and are described as having *early-onset dementia*. The two most common causes of late onset dementia – Alzheimer's disease and vascular dementia – are also the most common in people with early onset dementia, but there is a higher proportion from other causes (van der Flier and Scheltens, 2005). A study of 185 early-onset sufferers found roughly 34% of cases were Alzheimer's and 10% vascular dementia (Harvey et al., 2003) compared to 62% and 17% in older people (LSE PSSRU and the KCL Institute of Psychiatry, 2007). As with late onset dementia, prevalence of the early onset form increases exponentially with age, roughly doubling with every five year increase (Harvey et al., 2003). Other common causes of early-onset dementias are rare in the late-onset group – for example 10% of early-onset dementias are alcohol-related and genetic conditions such as Huntingdon's disease and Down's syndrome make a significant contribution (Harvey et al., 2003).

Despite 36 million people worldwide having dementia in 2010 (Wimo and Prince, 2010) there is no universally agreed definition for the term (Erkinjuntti et al., 1997). The American Psychiatric Association's Diagnostic and Statistical Manual of Mental Disorders IV, DSM-IV-TR, for example, required memory and at least one other cognitive function to be affected. The condition did not have to be progressive, but there must have been deterioration from a previous level of performance, and be serious enough to impact social interactions or work (American Psychiatric Association, 2000, page 148).

The World Health Organisation's International Statistical Classification of Diseases and Related Health Problems, ICD-10, defines dementia as affecting several mental faculties, such as reasoning or decision making, and might include memory, and unlike the APA's definition does not require any severity of impairment nor deterioration (WHO, 2015; Brämer, 1988).

DSM-5 was published in 2013, replacing DSM-IV-TR, and comes closer to the ICD-10 definition by dropping the requirement for memory loss, since this is normally absent in dementias such as Frontal Lobe Dementia, and no longer needs more than one mental function to be affected, although unlike the ICD definition it still emphasises decline (Remington, 2012; American Psychiatric Association, 2013, page 602).

But perhaps the most important change in DSM-5 was the replacement of "dementia" with a new name, Major Neurocognitive Disorder, to combat the stigma associated with the word "dementia" although there are suggestions that the new name will take on the same derogatory overtones as the old one (George et al., 2011; Remington, 2012; Mitchell, 2013).

1.2.1 Dementia in elderly people

There is considerable stigma associated with dementia because it combines several stigmatised conditions – ageing, mental illness and loss of independence (Scholl and Sabat, 2007; Graham et al., 2003; Corner et al., 2004; Harman and Clare, 2006). How people with dementia are viewed and treated by those around them has a massive effect on the sufferer (Kitwood, 1997). It is common for people with the condition to become depressed or suffer from low self-esteem, loss of status, anxiety or despair as a reaction to the diagnosis rather than as a symptom of the disease (Aggarwal et al., 2003; Bender and Cheston, 1997; von Kutzleben et al., 2012).

As the condition develops, the sufferer often struggles to understand and cope with the changes in a situation where their psychological capacity to adapt to these changes is itself affected by the illness (Woods, 2001). It is hard for others to understand what the sufferer experiences, although there are now a number of published works by both sufferers and close relatives describing the subjective experience of having dementia (Bryden, 2005; Henderson, 1998; DeBaggio, 2003; Davis, 1989; Magnusson, 2014; Stokes, 2010).

There are at least a dozen different scales which measure the degree of cognitive disability (Rikkert et al., 2011). One of the most widely used is the Clinical Dementia Rating (CDR) (Hughes et al., 1982) which assesses the person in six areas of cognitive disability to place them into one of four stages, plus a stage which corresponds to an absence of dementia. The stages are summarised in Table 1.1 and this simple scale is used throughout the thesis. Other commonly used scales are the Global Deterioration Scale (GDS) (Reisberg et al., 1982) and the Functional Assessment Staging scale (FAST) (Sclan and Reisberg, 2005), both are broadly similar but have more stages.

1.2.2 Causes and symptoms of late-onset dementia

Almost all late-onset dementia is caused by the diseases listed in Table 1.2, and there are both neuropathological and causal relationships between some of them. The table contains an estimate of the proportion of dementias caused by them, but for such a common condition there is a surprising amount of disagreement about the proportions because misdiagnosis and comorbidities are common – for example pathological signs of vascular dementia or dementia with Lewy bodies are frequently found in post mortems of people who were diagnosed in life with Alzheimer's disease (Shim et al., 2013; LSE PSSRU and the KCL Institute of Psychiatry, 2007). A brief description of each of the most common causes of dementia follows.

1.2.2.1 Alzheimer's disease (AD)

Alzheimer's disease is easily the most common cause of dementia, affecting about 62% of sufferers (LSE PSSRU and the KCL Institute of Psychiatry, 2007). Despite its importance there is still no proper understanding of the cause of the illness although considerable progress has been made in the last two decades. Whilst most sufferers are elderly, about 4% suffer from early onset, usually in their 40s or 50s (LSE PSSRU and the KCL Institute of Psychiatry, 2007).

CDR stage	Term	Features
0	"No dementia"	Normal abilities
0.5	"Questionable dementia"	Slight or borderline impairment which may even be imaginary. Fully aware of surroundings and able to carry out normal activities with minimal problems.
1	"Mild dementia"	Normal functioning impaired to some degree. Possibly some disorientation of time and location. Appears normal in casual social interactions. Needs help with more difficult activities.
2	"Moderate dementia"	Memory seriously impaired in the most common dementias. New memories quickly forgotten. Able to perform simple tasks independently but needs help with dressing, preparing food etc.
3	"Severe dementia"	Just scattered remnants of memory remain in the most common dementias. Unable to carry out trivial tasks.

Table 1.1: Summary of the Clinical Dementia Rating Scale (adapted from Hughes et al., 1982)

Cause	Proportion
Alzheimer's disease	62%
Vascular dementia	17%
Mixed	10%
Dementia with Lewy bodies	4%
Frontotemporal dementia	2%
Parkinsons disease	2%
Other	3%

Table 1.2: Causes of late-onset dementia in the UK (LSE PSSRU and the KCL Institute of Psychiatry, 2007)

AD is marked by large numbers of neurons dying, initially concentrated in the entorhinal cortex and the hippocampus but eventually spreading across the whole brain (Fox et al., 1996). As the hippocampus is intimately involved in episodic memory storage and recall (Milner et al., 1998), the earliest symptoms are normally difficulties remembering new information (Weintraub et al., 2012).

As the disease takes hold, the sufferer develops confusion about their whereabouts and time; and often becomes unable to find the correct words or phrases in speech. Eventually they can no longer name people or even familiar objects (Geldmacher and Whitehouse, 1996). By the time that they die, at a median of 4.2 years for men and 5.7 years for women after diagnosis (Larson et al., 2004), their brain may only be two thirds of the weight of a non-sufferer (LaFerla et al., 2007).

At the microscopic level neuron necrosis is accompanied by deposition of 120 μm to 200 μm diameter extracellular plaques (De Estable-Puig et al., 1986) – star-shaped balls of filaments largely composed of oligomers and monomers of two specific protein fragments (i.e. peptides), amyloid-β-40 and amyloid-β-42, together abbreviated to Aβ (Selkoe, 2001; Kuo et al., 2001; Roher et al., 1988; Atwood et al., 2002).

In addition, insoluble filamentous microtube structures composed of tau proteins are also present (LaFerla and Oddo, 2005; King et al., 2001; Selkoe, 2001). These neurofibrillary tangles (NFT) are present in other types of dementia too, but in AD they mostly form 10 nm diameter fibrils wrapped in pairs and twisted into helices called paired helical filaments (PHF) (Selkoe, 2001). Other pathological changes present include inflammation and oxidative stress (LaFerla et al., 2007). Both soluble tau proteins and Aβ are normally present in neurons, but it is the formation of the insoluble microscopic structures which is the key pathology in AD (LaFerla et al., 2007).

There is no effective treatment for AD, and although palliatives are available their effects are limited to slowing its progression for a few months. The most widely used are cholinesterase inhibitors to counter declining acetylcholine production (Contestabile, 2011; Scarpini et al., 2003).

Genetics is more important in early onset AD than the late onset form. Half of people with early onset dementia have familial Alzheimer's disease (FAD), caused by one of three gene mutations (LaFerla and Oddo, 2005). Whilst the genetic link is not so direct in late onset AD it is still important with more than twenty risk genes identified (Karch and Goate, 2014).

Obesity, hypercholestorlaemia or hypertension occurring during middle age, smoking, high alcohol intake (Deng et al., 2006), and lack of exercise are amongst the modifiable risk factors for acquiring the disease (Ballard et al., 2011; Pope et al., 2003) and it is no surprise that other diseases for which these are also risk factors – stroke and diabetes – are themselves risk factors for AD.

1.2.2.2 Vascular dementia (VaD)

After AD, the next most common cause of dementia is the restriction of blood supply in parts of the brain through blood clots, strokes or cardiac disease which leads to small scale infarctions (Román et al., 2002). The illness was historically called arteriosclerotic dementia (Loeb and Meyer, 1996; Strub, 2003), and was considered to be the underlying cause of most senile dementias until the 1970s when it was re-described as *multi-infarct dementia* by Hachinski et al. (1974). As neuroimaging developed and it became clear that there were several variants of the illness, the term vascular dementia was coined to cover them all, with multi-infarct dementia becoming a sub-type (Loeb and Meyer, 1996). Since dementia is only one of the possible effects of cerebrovascular damage, the term *vascular cognitive impairment* (VCI) now has widespread acceptance (Rockwood, 2002; Jellinger, 2005). The most common VCI condition is *vascular cognitive impairment–no dementia* (vascular CIND), which may be a prodrome of VaD (Pedelty and Nyenhuis, 2006).

Amongst the different types is *large-vessel vascular dementia*, in which larger cerebral arteries are affected triggering one or more strokes. If several sites are affected then this is *multi-infarct dementia* (Román, 2002), although dementia can also be caused if only one or two key sites such as the thalamus are damaged, with the resulting variant called *strategically placed infarct dementia* (Román et al., 2002). Damage to smaller arteries can cause *lacunar strokes* and *Binswanger's dementia*, both types of *small-vessel vascular dementia* (Román et al., 2002). Damage can also be caused by a series of temporary blood flow interruptions, often ephemeral blood clots, and called *transient ischemic attacks* or *mini-strokes*. Other subtypes include lesions caused by haemorrhages, deposits of amyloid-β peptides within blood vessel walls which weaken them (cerebral amyloid angiopathy), and genetically mediated dementias (Thal et al., 2012).

There are specific risk factors associated with VaD apart from age. These are generally the same as the risk factors for stroke and include hypertension, obesity, smoking, type 2 diabetes, high cholesterol and atrial fibrillation (Breteler, 2000; Bornebroek and Breteler, 2004; Biessels et al., 2006).

1.2.2.3 Mixed dementia

The high incidence of the most common diseases which cause late-onset dementia means that many sufferers have more than one of them. Whilst there is agreement that many dementia cases are mixed dementia, some authors have argued that the majority of elderly dementias are in fact mixed, particularly in the very old (Jellinger and Attems, 2010) and consequently that most lie somewhere between pure AD and pure VaD (Kalaria, 2002; Breteler, 2000). The similarity in symptoms, particularly mood and behaviour changes, and the lack of proper diagnostic criteria for mixed dementia mean that it is often misdiagnosed as either just AD or VaD (Jellinger, 2007; Agüero-Torres and Winblad, 2000; Groves et al., 2000).

There is even some debate whether some apparently different types of dementia are merely facets of a common underlying illness. AD sufferers often show considerable neurovascular damage and it shares the same metabolic syndrome risk factors as strokes and VaD. Lewis et al. (2006) found high concentration of amyloid-β-42 peptides in the brains of VaD sufferers.

Consequently, it has been suggested that AD may either be caused, or exacerbated, by vascular disease (de la Torre, 2002), and that although it has its own distinct neuropathology the best way of preventing or at least mitigating it is to address the modifiable risk factors for VaD, which are obesity, diabetes and heart disease since the same drugs, diets and lifestyle which provide some protection against VaD also help protect against AD (Breteler, 2000; Snowdon et al., 1997).

1.2.2.4 Dementia with Lewy bodies (DLB)

This disease has neuropathological similarities to AD, insofar as similar amyloid β plaques are found although no paired helical filaments. Instead, filaments of another protein, α-synuclein, are present, which are also implicated in Parkinson's disease (Jellinger, 2009).

The early cognitive problems of DLB are usually different from those seen in AD sufferers, since it is typically the portions of the brain controlling attention and visuospacial reasoning that are initially affected rather than those for memory which suffer at an early stage in AD (Simard et al., 2000; O'Brien, 2007).

The symptoms typically consist of impaired cognitive ability, realistic and persistent visual hallucinations in 80% of sufferers and the tremor and rigidity of Parkinson's disease in 50%, with fluctuating symptom severity in at least half of people (Barber et al., 2001). People with DLB also have far greater rates of auditory hallucinations and psychosis than in AD (Ballard et al., 1999). A useful diagnostic marker for the disease is the inability to copy simple drawings because of the early problems it causes with visuospacial reasoning (Tiraboschi et al., 2006).

1.2.2.5 Frontotemporal dementia (FTD)

Frontotemporal dementia is the second most common cause of early onset dementia, and far more common in people aged 45–65 than in older people (Hodges and Patterson, 2007), with only 20–40% of cases in people aged over 65. The symptoms are produced by *frontotemporal lobar degeneration* (FTLD), the degeneration of the frontal or temporal lobes which can also cause some other progressive brain diseases such as supranuclear palsy and amyotrophic lateral sclerosis (Snowden et al., 2002; Seelaar et al., 2011). Neuropathologically there are several histological types of FTLD determined by the presence or otherwise of inclusions of different insoluble proteins (McKhann et al., 2001; Seelaar et al., 2011).

FTD itself is classified into three types according to the dominant clinical symptoms, but share a common neuropathology. The most common, *behavioural variant FTD* (bvFTD), affecting half of sufferers, sees major changes in behaviour or personality and is associated with frontal and anterior temporal lobe atrophy (Seelaar et al., 2011; Josephs, 2008; Graham and Hodges, 2008). A family history of this variant is present in 30–50% of cases, although rare in the other two variants (Seelaar et al., 2011). Six different chromosomal defects have been implicated in bvFTD, with the most important two each responsible for 5–10% of cases (Rohrer, 2011). Higher level cognitive faculties are affected; for example the person may become emotionally blunted and unable to feel social emotions such as sympathy or empathy, develop disinhibited social behaviour, or develop compulsive or repetitive behaviour such as hand-rubbing or humming (Rabinovici and Miller, 2010; Snowden et al., 2002).

As the illness develops, the person can become extremely impulsive and unrestrained, for example eating food from someone else's plate during a meal or attempting to leave a moving vehicle when their attention is attracted by something outside (McKhann et al., 2001).

The second most common type is *semantic dementia* (SD), occurring in between quarter to a third of cases, and is associated with temporal lobe atrophy, particularly the left temporal lobe (Seelaar et al., 2011; Hodges and Patterson, 2007; Graham and Hodges, 2008). In contrast to the damage to the hippocampus seen in the early stages of AD, sufferers have no trouble recalling recent chronological memories but instead lose the ability to understand speech or even just find certain words. This quite specific memory loss becomes broader as the disease progresses, so that the sufferer can lose the ability to recognise or understand objects, faces or even smells (Josephs, 2008).

The rarest of the three types is *passive nonfluent aphasia* (PNFA) in which fluent speech production is impaired and is also associated with left temporal lobe atrophy (Seelaar et al., 2011; Josephs, 2008; Graham and Hodges, 2008). In many cases the symptoms of all types are present and the clinical type is classified according to the most dominant. Diagnosis is usually provisionally according to the symptoms and confirmed using brain imaging where lobe damage becomes apparent (Snowden et al., 2002).

1.2.2.6 Parkinson's Disease (PD)

Roughly 10% of Parkinson's Disease sufferers develop DLB-like dementia each year (Aarsland and Kurz, 2010). PD is a degenerative disease caused by destruction of dopamine-producing neurons in the substantia nigra pars compacta, a midbrain region concerned with motor control (Fearnley and Lees, 1991). As dopamine production declines the sufferer develops a tremor and difficulty moving. The illness is idiopathic in about 85% of cases, with the remainder having a likely genetic connection with an immediate relative with a history of the illness (Samii et al., 2004). About a dozen different genetic mutations have been identified which can cause PD, and another six identified as risk factors (Schulte and Gasser, 2011).

1.2.2.7 Conclusion

Most dementia is caused by a small number of illnesses. Whilst some have intriguing pathological similarities, such as the presence of Aβ or tau protein structures, there is no single cause. It would be a mistake to assume that all people with dementia have similar symptoms. For example, whilst most dementias affect memory in some way at an early stage, some types such as bvFTD, often leave memory intact.

1.2.3 Diagnosis

Diagnosis of dementia is usually by a standardised screening test, such as the Mini-Mental State Examination (Hansen et al., 2008). This is usually performed a result of behavioural changes reported by family members, or observed by the GP, rather than memory problems (Hansen et al., 2008), and the diagnosis is frequently concealed from the patient and only given to family members or caregivers (Hansen et al., 2008; van Hout et al., 2000).

Since the affected cognitive functions differ with the underlying disease, the symptoms are used with variable reliability to identify that illness (Meulen et al., 2004). For example, the early signs of AD normally include problems assimilating and recalling new memories; whilst frontotemporal dementia initially affects personality rather than memory. Other supporting evidence can sometimes be found to confirm the diagnosis, for example by chromosome tests if there is a familial history of AD.

Diagnosis is complicated by comorbidities (van Hout et al., 2000), and mild dementia is easily confused with age related cognitive decline; in a systematic review of six studies van den Dungen et al. (2012) reported diagnostic sensitivities of 0.09 to 0.60 for GPs, and Bond et al. (2005) recorded that 70% of doctors believe that GPs had difficulty recognising the early stages, and 35% that specialists also had difficulty. The same study found that it took on average 32 months for someone in the UK to be diagnosed with dementia following the first symptoms being noticed by a carer. Not surprisingly there is ample evidence that less than half of people with dementia receive the correct diagnosis (Macdonald and Carpenter, 2003; Eustace et al., 2007).

Dementia is clearly not the only major health problem which disproportionately affects elderly people. Osteoporosis coupled with factors such as gait, postural hypotension or sensory problems makes injurious falls far more common in this group than in the rest of the population (Rubenstein, 2006; Boele van Hensbroek et al., 2009). A specific diagnosis of dementia is associated with an increased risk of falling of about double (Eriksson et al., 2008; van Doorn et al., 2003), and having carried out a brief survey of dementia we will now turn to the problem of falls.

1.3 Falls in elderly people

Falls are a serious problem for the elderly, and for people over 75 the most likely cause of fatal injury (Masud and Morris, 2001). One study suggested that adults aged 75–79 had a mean of 0.65 falls per year, and 80–84, 0.94 falls per year (Campbell et al., 1990). 13.5% of people aged 65 or more attending hospital emergency departments in the US during 2009–2010 did so because of falls (Albert et al., 2013). Just over half (56%) of 27 studies showed an increased fall risk for people who suffer from a cognitive impairment (Muir et al., 2012) and this included even people with a mild impairment.

Not only do elderly people have a greater risk of falling than the general population, which is discussed in this section, but the consequences are often much more serious, and discussed in Section 1.3.1. Some of the most important reasons why falls are relatively common in elderly people are shown in Table 1.3. A few are particularly significant – reduction of muscle mass, deterioration in sensory perception from subcutaneous touch sensors (Maki et al., 1999) and in motor control, and the effect of medications (Gibson et al., 1987).

People lose muscle mass as they age at a rate of about 1% per year, a process called *sarcopenia* (Mühlberg and Sieber, 2004). The reduction in strength makes them less able to apply sufficient force to stop a fall and also reduce both the speed and limits of limb movement. At the same time reduced mobility, which may be exacerbated by arthritis, causes neuromotor control to deteriorate because muscles are less exercised and this can cause problems with balance and gait. Good neuromotor control helps muscles to impart large forces quickly (Perry et al., 2007; Skelton et al., 2002), especially if they are near the limit of the muscle's capacity.

About half of falls in elderly people cause injury, with 10% causing a serious injury such as a bone fracture (Masud and Morris, 2001). Minor injuries such as abrasions and bruises, which do not require first aid, occur in perhaps 40% of falls (Vellas et al., 1998).

Insufficient lower limb muscle strength
Lower limb joint or nerve problems
Balance, vestibular system defects
Gait problems
Cognitive impairments
Eyesight or other sensory impairments
Inadequate motor coordination
Medication side effects such as dizziness
Breathlessness, respiratory problems
Postural hypotension and other cardiovascular
Postural/skeletal problems, such as kyphosis

Table 1.3: Some common intrinsic causes of falls in elderly people (adapted from Sinaki, 2004; Berg et al., 1997)

1.3.1 Why falls are so damaging to elderly people

The most serious factor for injury once hitting the ground is inevitable is osteoporosis since this reduces bone toughness and strength, particularly affecting the trabecular bone microstructure which is heavily concentrated in load bearing areas such as the femur, the spine and the wrist (Bartl and Frisch, 2004). Osteoporosis can so weaken bones that falling less than a metre onto a major bone can cause a fracture. At the same time sarcopenia reduces the surrounding muscle bulk which pads and protects the bones.

Bones are mostly made from calcium hydroxyapatite and have a complex heterogeneous internal structure (Cummings, 2002; Bartl and Frisch, 2004). In small bones the hydroxyapatite is arranged as a dense solid mass called *cortical* (or *compact*) bone, and in larger bones this forms a shell surrounding a far less dense interconnected sponge-like formation called *trabecular* (or *cancellous*) bone. Trabecular bone is composed of interconnected irregularly shaped microscopic rods and plates 1 mm to a few millimetres long and 0.1 mm to 0.5 mm thick, called *trabeculae*, with the spaces between them filled with marrow tissue. The alignment of trabeculae appears random at a microscopic level, but at the macroscopic one is preferentially aligned with lines of maximum stress under the bone's usual loading.

As bone is mechanically stressed over long periods it develops microscopic fatigue cracks which would weaken it if allowed to grow (Lee et al., 2000). To prevent this, bone is constantly being renewed by a process called *remodelling* in which the inorganic material is dissolved and replaced (Cummings, 2002).

However, during adult life the bone generation rate does not quite keep up with the removal rate. This is particularly severe for women immediately following menopause since oestrogen inhibits the bone removal, and the immediate decline in hormone concentration increases bone resorption rates and can result in loss of 1-3% of bone mass per year. 3-5 years after menopause the rate of bone loss falls again to a level maintained until the seventies when it picks up to about 1% per year. In consequence, a woman in her eighties might only have half the bone mass that she had in her twenties (Cummings, 2002). Men also suffer from osteoporosis but to a lesser degree, although it can be exacerbated by several medical problems (Mosekilde et al., 2013).

Osteoporosis manifests itself as a thinning of cortical bone but a much more serious erosion of trabecular bone – in the bones of someone with advanced osteoporosis, half of trabecular bone may have gone and those "plates" and "rods" which remain are smaller with some rods no longer connecting to a second fragment of bone. The reason for the difference in erosion rates is probably because a quarter of trabecular bone is remodelled annually compared to only a few percent of cortical bone (Bartl and Frisch, 2004).

Most bone is cortical, with only 20% trabecular, although specific bones contain high proportions of trabecular bone and become much more fragile – for example the lumbar vertebrae contain 75%, the proximal femur 50-75% and distal radius 25% (Bartl and Frisch, 2004). The most common osteoporotic injuries are vertebral fractures, which occur in nearly half of women and 20% of men by age 90 but are often undiagnosed (Cummings, 2002). Between 50 and 79, men have roughly a 0.6% per year chance of sustaining such a fracture compared to women with 1.1% (European Prospective Osteoporosis Study (EPOS) Group et al., 2002).

Vertebrae often become crushed because they have a high proportion of trabecular bone coupled with high compressive loading, often leaving the top and bottom surfaces of the vertebrae no longer parallel to each other (Ismail et al., 1999). A common result is a slight hump backed deformity called *kyphosis* seen in many very old people. As well as causing a considerable amount of pain and disability in itself kyphosis can also cause gait abnormalities which make a fall more likely (Sinaki, 2004).

1.3.2 Injuries caused by falling

The types of injuries caused by falling are shown in Table 1.4. A serious injury resulting from a single fall often heralds far-reaching physical decline (Tinetti and Williams, 1998). Even without causing an injury a fall is frequently associated with a decline in the ability to undertake activities of daily living over the next few years, and experiencing multiple falls deters many people from undertaking even social activities.

Even if the fall doesn't seriously injure the person, they may be at serious risk from the effects of lying on the ground for any length of time. There is a strong correlation between the amount of time that someone lies helpless after falling and mortality both as an immediate

Result	Percentage
No injury	40–60
Minor injury	30–50
Hip fracture	1
Other bone fracture	4
Major non-fracture injury	5–6

Table 1.4: Physical effects of falling (adapted from Masud and Morris, 2001)

consequence and subsequently. Gurley et al. (1996) looked at 387 falls in San Francisco which paramedics had attended and reported that 10% of fallers who had been incapacitated for an hour or less before help arrived were found dead, whilst 62% had died where help had not arrived within 72 hours. 2% of the people who had laid for an hour or less later died in hospital of their injuries, compared to 5% of those who had spent 72 hours lying – i.e. 13% of the longer lay survivors died shortly afterwards compared to 2% of the short lay survivors. Wild et al. (1981) found that half of the 20 people who had lay for more than an hour, a "long lie", died within six months even though none had suffered from hypothermia. In a systematic review of the few studies available, Bloch (2012) found an odds ratio of 1.75 for early death (95% CI = 1.15–2.67) of people who had lain on the ground for an extended period. Even without a fracture there are many reasons why a long lie can be dangerous, hypothermia, renal failure, dehydration, pressure sores, rhabdomyolysis and reduced potassium levels (Bloch, 2012; Bloch et al., 2009).

Those 50% of fallers who are not injured may still find the fall life-changing since it often induces a chronic fear of falling, which frequently leads to depression and self-imposed restrictions on the types of activities that the person is prepared to undertake, perhaps making them less willing to go out or walk. Fear of falling is usually measured using the Falls Efficacy Scale (Tinetti et al., 1990), which asks the individual to rate each of 16 activities, such as getting dressed or walking somewhere where there are crowds, with a four value Likert scale. It is not clear how many people have a fear of falling, with estimates ranging from 20% and 85% (Tinetti et al., 1990), although about half of those who have a strong fear have never personally suffered a serious fall themselves (Scheffer et al., 2008).

1.3.2.1 Hip fractures

Amongst the common fractures caused by falls, hip fractures are particularly serious since they often have catastrophic consequences in contrast to the other types, such as wrist fractures. They occur in about 1% of falls (Masud and Morris, 2001) but are responsible for 65% of people over 75 hospitalised following a fall (Sartini et al., 2010).

Hip fractures are thought to be caused by falling when stationary or walking very slowly (Cummings and Nevitt, 1989). When one leg collapses the individual will land on their side, where the most common impact point is the greater trochanter, the muscle attachment protrusion near the top of the femur on the outer surface (Parkkari et al., 1999). By contrast, higher speeds tend to throw people forwards, where they often try to stop the fall with their hands which frequently results in a particular fracture of the distal radius, called a Colle's fracture (Palvanen et al., 2000).

Fractures following a fall onto the greater trochanter are usually in the top part of the femur, either the femoral neck – the connection to the hip joint – or just below the greater trochanter. Each occur in about 45% of cases, with a fracture further down the femur, within a few centimetres of the lesser trochanter – a small protrusion underneath the femoral neck – occurring in only 5–10% of cases (Kyle et al., 1995; Zuckerman, 1996). A femoral neck fracture is difficult to treat if it occurs inside the articular capsule since the bone here is poorly vascularized and any displacement can damage or kink blood vessels feeding the femoral head. This can stop the fracture from healing properly or cause femoral head necrosis. Even if the fracture is outside the articular capsule, the person may still haemorrhage up to a litre of blood (Parker and Johansen, 2006). Although easier to treat, Keene et al. (1993) found that extracapsular fractures tend to occur in slightly older people (mean 80 rather than 78) who are more frail and consequently have a higher mortality and morbidity than intracapsular ones.

A systematic review by Abrahamsen et al. (2009) of 22 studies found that all reported at least a doubling of the mortality risk over the first year compared to age matched controls. The first six months is the most dangerous period, with 70% of deaths occurring within it, and 25-33% within the first month (Abrahamsen et al., 2009). Mortality rate increases with age, for example Holt et al. (2008) reported a 30 day mortality rate of 3% for age range 60–69 and 8% for 80–89. However, the relative risk actually declines because the general population suffers from increasing mortality rate with age (Abrahamsen et al., 2009).

In their study, Roche et al. (2005) reported that around 10% of people over 65 who undergo surgery following a hip fracture die within 30 days, rising to a third after a year corresponding to an excess mortality of 20% over the year. Chest infections and coronary failure are the most common complications, occurring in 5% and 9% of cases respectively. They are also the most lethal with a mortality after one year of 72% and 92% in the people who suffered them (Roche et al., 2005). The increased mortality continues for several years, Haentjens et al. (2010) found an excess mortality of 20% a decade later for people who fractured their hips in their eighties.

Women are three times more likely than men to suffer a hip fracture, probably because of the much greater incidence and severity of osteoporosis (Abrahamsen et al., 2009) and the incidence of hip fractures has sometimes been used as a surrogate for osteoporosis in epidemiological studies (Kanis et al., 2012).

Osteoporosis can so weaken bone that poorly coordinated muscle contraction is enough to break it, and 5-10% of hip fractures are thought to be spontaneously caused in this way. People who suffer these fractures often report that severe pain occurred just before the fall (Viceconti et al., 2012; Tinetti, 2003; Parker and Twemlow, 1997).

Whilst spontaneous hip fractures account for a small proportion of falls, the majority are caused by other incidents, and these are the subject of the next section.

1.3.3 Events that trigger a fall

Williams et al. (1998a) classified falls into *intrinsic* ones, caused by medical conditions such as syncope, and *extrinsic*, caused by trip or other hazards outside of the person's body. This is probably overly simplistic, since a trip over an extrinsic hazard may occur, or be converted into a fall, for an intrinsic, medical reason.

Rubenstein and Josephson (2002) reviewed 12 studies which looked at the causes of falls, containing a total of 3628 falls, half of which were of people living in the community and half in care homes.

Four causes accounted for 70% of falls. The most important were accidents such as trips, accounting for 31%, with other three being problems with walking or maintaining postural stability (17%), vertigo or dizziness (13%), and drop attacks – abrupt and unexpected falls whilst remaining conscious. No other cause accounted for more than 5%. However, there was a considerable variation between the studies, for example the proportion of falls allocated to the vertigo and dizziness category ranged from 0% to 30% according to the study. The authors found comparing studies difficult for several reasons, such as differing methodologies, participant types, and because a fall often has several causes acting in sequence. An example of a chain is an obstruction which is not seen because the individual has poor eyesight, and whose shuffling gait then causes them to trip, and they are unable to arrest the fall because of impaired balance. The fall could be equally classified as having been caused by the environment, eyesight, or impaired walking or postural stability.

Men are more likely to fall outside than women, often during gardening and similar activities with 25% of men's falls occurring in the garden compared to only 11% of women's (Masud and Morris, 2001; Campbell et al., 1990; Berg et al., 1997), and people aged under 75 are more likely to fall outside than those over this age possibly because they go outside more. Only 11% of falls in women occur in the garden, compared to 25% for men (Masud and Morris, 2001). About 60% of falls in community living women aged 70 or more occur inside their home (Nachreiner et al., 2007) usually in the living room, kitchen or bedroom with surprisingly only 3% in the bathroom with its potentially slippery floor. Stairs are understandably dangerous with 22–28% of indoor falls occurring there (Nachreiner et al., 2007; Bleijlevens et al., 2010). Walking is a common activity immediately preceding a fall, occurring in 21% (Bleijlevens et al., 2010) to 54% (Nachreiner et al., 2007) of cases. In an interesting study Robinovitch et al. (2013) placed video cameras in public areas of a nursing home and recorded 227 falls in a very elderly population (mean age 78, standard deviation 10 years). Here 24% of falls occurred whilst walking, 13% whilst standing still and 12% during the process of sitting down. This is not the first time this approach has been taken, as it was tried on a much smaller scale using videotape recorders in the late 1980s but only 25 falls were recorded (Holliday et al., 1990).

The arrangement of the surfaces where falls occur has also been studied; for example in one large study based on the examination of Australian hospital accident department records, 54% of falls of people 65 or older occurred on the same level, whilst 9% of falls of people aged 65-79, and 5% of people aged above 80, were on stairs (Mitchell et al., 2010).

1.3.4 What is a fall?

Different authors have different ideas about what a fall is, which often causes problems when trying to compare or aggregate results of different studies. Researchers and medical professionals often have different views to elderly people of what a fall is and this can lead to errors in data collection. Zecevic et al. (2006) found that the people aged 55 and over tended to define a fall in terms of the events which surround it – a fall inducing event such as a stumble followed by a consequence such as losing balance, hitting the ground or getting hurt. One person described a fall as "Trip over rug and go down and injure yourself". By contrast medical professionals tended to emphasise the outcome; for example an injury or the part of the body striking the ground.

Definitions in research literature look more at the fall itself, ignoring the circumstances which cause it and often with explicit exclusion criteria. Whilst fallers themselves do not generally report falls in which they were not hurt, the definitions rarely explicitly exclude them and some take care to ensure they are included (Zecevic et al., 2006). An example of this is:

> "an event in which the resident unintentionally came to rest on the floor, regardless of whether or not an injury was sustained. This definition included falls as a consequence of acute illness such as a stroke or an epileptic seizure."
>
> (Eriksson et al., 2008)

Researchers tend to focus on those types of fall relevant to their particular study and exclude irrelevant falls. For example, someone studying the cause of injurious falls might include falls resulting from a loss of consciousness, whilst another who is evaluating techniques to strengthen muscles or improve motor coordination would exclude them. These varying definitions can make comparing or aggregating different studies difficult (Hauer et al., 2006b), and oversimplify multiple or unknown causes for a fall.

A systematic review of randomised fall prevention trials by Hauer et al. (2006b) found two quite different definitions in wide use. One, the Frailty and Injuries: Cooperative Studies of Intervention Techniques trials definition was also found to be the most common definition across 58 studies examined during the preparation of the 2013 NICE Clinical Guidelines on fall prevention (Centre for Clinical Practice, 2013), and defines a fall as

> "unintentionally coming to rest on ground, floor, or other lower level; excludes coming to rest against furniture, wall, or other structure."
>
> (Buchner et al., 1993)

The other was produced by the Kellogg International Working Group on the Prevention of Falls in the Elderly:

> "an event which results in a person coming to rest inadvertently on the ground or other lower level and other than as a consequence of the following:
> Sustaining a violent blow.
> Loss of consciousness
> Sudden onset of paralysis, as in a stroke.
> An epileptic seizure." (Gibson et al., 1987)

One or other of these definitions was cited in 17 of the 90 papers examined, although 11 used a modified version (Hauer et al., 2006b). No other paper used a cited definition, and about half, 44, did not provide any definition.

There is no agreement on what a fall is, which makes the design of a fall detector to detect "all falls" theoretically questionable. Most research into falls, at least outside of fall detection, is not really about the falls themselves, but either their precursors or consequences. For a fall detector the urgency of summoning help must depend upon the injury or harm the person is suffering, which unless the fall's precursor was a medical emergency, must depend upon the consequences.

Risk factor	Relative Risk or Odds Ratio	Relative Risk Range
Muscle weakness	4.9[a]	1.9–10.3
Balance problems	3.2[a]	1.6–5.4
History of falls	3.0[b]	1.7–7.0
Gait problems	3.0[a]	1.7–4.8
Visual problems	2.8[a]	1.1–7.4
Use assistive device	2.6[b]	1.2–4.6
Limited mobility	2.5[a]	1.0–5.3
Cognitive impairment	2.4[a]	2.0–4.7
Impaired activities of daily living	2.3[b]	1.5–3.1
Physical disability	2.0[a]	1.0–3.1
Postural hypotension	1.9[a]	1.0–3.4
Age > 80	1.7[b]	1.1–2.5
Medication (especially psychoactive)	not specified[a]	1.5–1.7

[a]Taken from a review of 16 controlled studies in Rubenstein (2006)
[b]Additional risks taken from a review of 16 multiple risk studies in Rubenstein and Josephson (2002)

Table 1.5: Risk factors for falls in elderly people (Combination of data from Rubenstein, 2006; Rubenstein and Josephson, 2002)

1.3.5 Risk factors and fall prevention

Preventing falls is the best way of minimising the harm caused by them, and considerable effort is expended on identifying and, wherever possible, mitigating the risk factors (Edwards, 2011). Age is the most important factor for an injurious fall in terms of numbers of people affected, followed by having previously had a fall, with about half of fallers having recurrent falls (Masud and Morris, 2001). The risk factors identified from a review of 16 controlled studies are shown in Table 1.5, with additional ones not covered by the first review added from a second review which looked at multiple risk factors.

Additional risk factors not in the table have been identified in limited studies, for example urinary incontinence (see Chiarelli et al., 2009, for a systematic review) probably for several reasons – the urgency to get to the toilet coupled with poor night time lighting, drowsiness, orthostatic hypotension from rapidly standing, and poor sleep patterns caused by the condition.

Forster and Young (1995) tracked falls in 108 stroke patients and found that 21% of them had fallen in the 12 months before the stroke, compared to 73% who fell in the six months following their discharge from hospital. Other risk factors are age of 87+, BMI of 24.7–27.2 kg/m^3, along with previous falls and fractures (Vellas et al., 1998).

The current NICE guidelines on fall prevention recommend strength and balance training, as balance, gait, Tai Chai and other functional training have all been shown to be effective for people living in the community (Gillespie et al., 2012; Schleicher et al., 2012; Centre for Clinical Practice, 2013). Although exercise is effective in sub-acute hospital wards, the results are inconclusive for long term care facilities, perhaps because the people are frailer (Cameron et al., 2010). The evidence that these interventions are effective for people with cognitive impairments such as dementia is weak (Hauer et al., 2006a; Oliver et al., 2007).

Pharmaceutical interventions can also help – reviewing existing medication to reduce psychotropic drug dose is effective for people both in nursing care and living in the community (Gillespie et al., 2012; Cameron et al., 2010). At the same time hormone replacement therapies are effective in increasing bone mineral density in post-menopausal women, and oestrogen-based hormone replacement therapies have given way to safer alternatives such as bisphosphonates, raloxifene and teriparatide which do not increase the risk of thrombosis and breast cancer (Huot et al., 2008).

The evidence for other medications is weaker but vitamin D and calcium dietary supplements can reduce injuries and falls by increasing muscle strength, joint mobility and bone mineral density (Bischoff et al., 2003) although vitamin D alone does not help except for people who are actually deficient in this vitamin (Gillespie et al., 2012). Cochrane reviews found that vitamin D and calcium supplements may reduce the incidence of falls and hip fracture in institutional settings (Cameron et al., 2010; Avenell et al., 2009) but there is no real evidence for people living in the community (Gillespie et al., 2012).

A few people are prone to falls because they suffer from cardioinhibitory carotid sinus hypersensitivity, in which gentle rubbing or other stimulation of the neck dramatically reduces blood pressure, and this can be treated effectively by fitting pacemakers (Gillespie et al., 2012).

Improving eyesight has mixed results – cataract surgery on the first eye for people who have cataracts in both eyes is beneficial but replacing bifocal glasses with uni-focal glasses reduced falls in people who were active enough to frequently go outside, but actually increased falls outside in people who rarely ventured out of doors (Gillespie et al., 2012). Perhaps improved vision makes people less cautious.

Making the living space safer, for example by assessing and removing trip hazards, is effective in reducing falls in people living in the community, particularly amongst those who had fallen previously and especially when this is performed by a physiotherapist (Gillespie et al., 2012).

Yielding floor surfaces can significantly reduce the risk of a hip fracture – a fall onto a carpeted wooden floor has half the probability of fracturing a hip as one onto either an uncarpeted wooden floor or a carpeted concrete floor (Simpson et al., 2004).

Hip protectors can also reduce the injury caused in a fall and are either rigid plastic (*hard protectors*) fitted into purpose-made underwear, foam filled pads (*soft protectors*) or a combination of both (Gillespie et al., 2010). However, getting people to wear them is difficult, particularly for people who are living in the community who are less supervised. They are not particularly comfortable, especially in bed, adversely affect appearance and the effort required to wear them is often not judged worthwhile by the people at most risk (Cameron and Quine, 1994). Nevertheless, Oliver et al. (2007) found that they did have a modest beneficial effect on injury in care home residents.

1.3.6 Dementia and falls

Many studies show that people who have been diagnosed with dementia are two or three times as likely to fall than those of a similar age without cognitive disorders (Eriksson et al., 2008; van Doorn et al., 2003; Morris et al., 1987). van Dijk et al. (1993) found that people with dementia within a nursing home had an average of 4 falls per year, with men far more likely to fall than women – with men in their late 70s averaging 8.9 falls per year and women of the same age group having "only" 3.3 falls. The likelihood of falling did not increase with age, rather it initially increased with the degree of physical or mental disability and then declined, perhaps reflecting the reduced mobility of people with more severe dementia or age related disability. This contrasts with the finding by Campbell et al. (1990) of 0.65 falls per year for community dwelling adults in this age range.

Struksnes et al. (2011) questioned nurses working in four dementia care facilities about the reasons that their patients fell, and the most common are shown in Table 1.6. It is striking how important forgetting about impairments was given as a factor.

Impairments in gait and balance are common in AD (Mazoteras Muñoz et al., 2010; Thomas et al., 2002) and even more so in other common dementias (Allan et al., 2005). Psychotropic medication (Shaw and Kenny, 1998) can also increase the likelihood of falling and people with dementia can also suffer from greater environmental problems – Clemson et al. (1996) found that the homes of people with cognitive impairments had more environmental hazards than other people.

Other reasons include orthostatic hypotension, which is more common in people with dementia (Mehrabian et al., 2010) and a failure of the person to understand their physical limitations – perhaps as a consequence of cognitive impairment. Behavioural problems such agitation and wandering (Shaw, 2007) can also be indirect causes of a fall.

Eriksson et al. (2008) looked at 103 people with dementia (and 83 without) in residential care and found that for those with dementia the likelihood of falling actually decreased as

Cause of falls	Mean Likert value	Std dev
Forgetting about impaired physical ability	3.0	0.8
Unable to call for help	2.8	0.8
Anxiety	2.8	0.9
Impaired body or movement coordination	2.7	0.8
Physical mobility	2.7	0.9
Poor distance estimation	2.5	0.8
Dizziness	2.5	0.8
Vision impairment	2.4	0.7
Lack of staff	2.4	0.9
Misunderstanding instructions	2.3	0.9
Forgetting about cognitive impairment	2.3	0.9
Forgetting about capacity to undertake ADL unaided	2.3	0.9
Likert scale: 1 = seldom, 2 = sometimes, 3 = often, 4 = very often		

Table 1.6: The most common reasons for falls in dementia care facilities, as expressed by nursing staff (adapted from Struksnes et al., 2011)

cognitive impairment increased, speculating that this was due to the reduced inclination and ability to walk as the condition progressed. Other important factors were taking four or more drugs, vitamin B12 treatment (used for anaemia) and being a man who uses a walking aid. The authors suggested that the walking aid may encourage hazardous behaviour in men through risk compensation. Medication use is a risk factor because of side-effects from psychotropic drugs such as anti-convulsants and narcotic analgesics (Kelly et al., 2003). Other factors include darkness, anxiety or not wearing shoes – the latter particularly for people over age 81 (Eriksson et al., 2009).

People with dementia are often excluded from falls prevention studies, and so much of the effort in this area may be inapplicable to them, but there is evidence that these strategies are less effective in people with impaired cognition (Jensen et al., 2003; Gillespie et al., 2012; Shaw, 2007, 2003).

The previous sections in this chapter have reviewed dementia and falling, and this section discussed how dementia is an important risk factor for falling. A fall is easily the most likely cause of serious injury for someone with dementia who is left alone. Rowe and Fehrenbach (2004) examined in-patient records for injuries sustained at home by people with dementia and found that 96% were caused by falls. Whilst fall prevention is the ideal way of dealing with the problem, falls will inevitably occur. An effective way of summoning help is needed, and the following sections discuss the technological means for doing this.

1.4 Fall detectors

Ambulatory fall detectors – electronic devices which alert a carer if someone falls – have been around for twenty years, and this section describes the current state of these devices and looks at the problems with them for people with dementia. Fall detection is only part of the solution, reducing injury when someone falls and preventing falls occurring or reoccurring are also important, but fall detection is particularly relevant for people with dementia because fall prevention may be less effective than in the elderly population generally.

Brownsell and Hawley (2004) found that fall detectors have a role to play in reducing the fear of falling in some people – whilst they can increase wearers' confidence that they will receive timely assistance, they can also sensitise people to the risks of falling and so increase their concern, although limitations in the study, such as the sample size and the recruitment method, make it difficult to make quantitative generalisations (Stewart and McKinstry, 2012).

Fall detectors are normally just one component of a social care system, which can include manually activated alarms, gas and flood detectors and pressure sensitive mats. The installation usually has a base station in the home that communicates by short range radio link with the other devices. The base station in turn communicates alerts generated by these devices by land line to a call centre, called an Alarm Receiving Station (ARC) in the ISO EN 50134 standards, whose operators can usually initiate two way communication using a microphone and speaker built into the base station or alert local carers.

Several authors (Martin et al., 2006; Siotia and Simpson, 2008; Ward, 2012) classify fall detectors, and assistive living alarms generally, into first, second and third generation devices. First generation fall detectors are the manually activated devices either worn on the body (for example on a wrist-band or a cord around the neck) or mounted on the wall.

Second generation devices automatically raise the alarm if they detect a fall. They can either be worn on the body or integrated into the fabric of the building – ambient, or context-aware (Syngelakis and Collomosse, 2011; Igual et al., 2013) systems, for example Willems et al. (2009) describes detection techniques which use a video camera. Whilst the vast majority of commercial fall detectors are wearable devices, ambient systems are more common amongst experimental projects. Igual et al. (2013) identified 130 papers since 2005 describing wearable devices, 176 describing context-aware systems and 21 which combined both approaches.

However, most ambient systems attempt far more than just fall detection since their sensors provide such a rich source of data that they open up much more ambitious possibilities. The normal goal is to monitor several health-related aspects of the person's life rather than just looking for falls. These are third generation systems – or lifestyle monitoring systems (Ward, 2012) – which use a range of sensors installed in the environment combined with pattern matching techniques to make inferences about an individual's health and well-being. The intention is often that the system does not just react to an emergency but can also proactively provide early warnings of an impending problem (Martin et al., 2006). For example it may be able to warn that the risk of someone falling has increased because of physical decline, perhaps detected through monitoring changes in gait and speed of movement.

Whilst there are many third generation research projects there are only a few, rather limited, commercial systems available. The greatest challenge is reliably drawing the correct conclusions from sensor data. Complex sensor networks are also expensive to install, particularly if each sensor requires hard-wired power or network connections, and presenting the information that it generates in an easily understandable manner to carers also causes difficulties. There is a vigorous debate about the impact of continuous automated surveillance on privacy, for example the degree to which they may cause people to modify their behaviour to prevent the intrusion of carers or medical staff (Weber et al., 2012; Chiapperino et al., 2012; Sorell and Draper, 2012).

There is an increase in complexity and sophistication with each generation – first generation systems sense and merely report a single alarm button whilst the second generation fall detectors carry out some specific and limited computations on data from one or two simple sensors. Third generation systems employ complex pattern matching techniques (or sometimes require the carer to do so) to handle the random variations in people's behaviour and overcome the challenges of making deductions using data combined from several types of sensors.

1.4.1 Commercial fall detectors

1.4.1.1 First generation, Personal Emergency Response Systems

The most common, and oldest, type of commercial "fall detector" is the wearable manually triggered personal emergency response system (PERS), often called a *pendant alarm* (Dewsbury and Linskell, 2011; Forster and Young, 1995). Allied to these are the fixed wall mounted alarms activated using a pull-cord which are the ambient equivalents of the wearable alarms. Wearable personal emergency response systems devices have been commercially available since the mid-1970s (Robinson, 1991), and are usually worn on the wrist, clipped onto clothing or on a cord around the neck (Hessels et al., 2011). They have a button which the wearer can press if they fall over or have some other problem, which alerts a remote monitoring centre. In some models the device's radio link allows the wearer to converse with the monitoring centre operator, but often this is done using an intercom connected to the telephone line in the home. The monitoring centre can then phone a carer or the emergency services if necessary (Fallis et al., 2007).

These devices suffer from several problems. They cannot be used by an unconscious individual, nor by many with serious cognitive impairments. For example, someone with moderate dementia may not remember that they have the device or even what it is for (Holliday, 2012). Compliance is a problem even for those people able to use them – for example the devices are often removed before going to bed so they may be left sitting beside the bed if the person gets up in the night. A surprisingly high proportion of users do not raise an alarm when they would be able to do so after a fall. The reasons for this behaviour include not wanting to trouble a carer, being unsure about the severity of their situation (De San Miguel and Lewin, 2008) or just being unable to operate the alarm (Fleming and Brayne, 2008).

In one study of 141 people aged 90+ who had fallen and not been able to get up afterwards, 113 (80%) did not to use their alarms, which were fixed alarm units in about two thirds of the cases and the rest wearable pendant alarms, with 13 people having both. Only one of the 38 people who lay on the floor for more than an hour used their alarm. This individual lay on the floor for so long because it took them more than an hour to crawl across the room to the alarm pull. A second person, who may have lay for more than an hour, used their alarm but was excluded from the 38 since the amount of time was indeterminate (Fleming and Brayne, 2008). Another study found that 12 out of 15 fallers wearing a PERS alarm did not activate it. Thirteen had remained on the ground for more than five minutes (and two longer than an hour) and of these 11 did not use their alarm (Heinbüchner et al., 2010). Eight people chose not to use their alarm for reasons of independence, another because they were already waiting for someone to come and help, and the remaining person just forgot about their alarm.

The next section looks at automatic fall detectors, which address the serious problem of the alarm not being manually activated.

1.4.1.2 Second generation, Automatic fall detectors

Almost all automatic fall detectors are wearable devices conceptually similar to PERS alarms. The simplest look for a single characteristic of a fall such as the person's body tilting from vertical (Holliday, 2012). These devices are usually worn at the waist and contain a tilt sensor which activates the alarm if it tilts to an angle of 60° to 70°. Because this is such a common occurrence, for example when lying down, the alarm typically vibrates for several seconds before activating. This warns the wearer of the impending activation to allow them to cancel it, normally by pressing and holding a button for several seconds.

To reduce the false positive alarms many designers treat the fall as a sequence of discrete events called *phases* – for example the free fall, the impact, and the period following it, and the alarm is triggered when it detects a sequence of features of each phase. The earliest device of this sort described in peer-reviewed literature (Williams et al., 1998b) consisted of a device worn at the waist containing a piezo-electric shock sensor and a mercury tilt switch. If it detected an impact above a threshold value then it would interrogate the tilt switch to see if the wearer was still standing, specifically if their torso was still vertical. If the tilt switch indicated that it was not then it would wait twenty seconds for them to stand up, and if the tilt switch still showed them to be lying down it would transmit an alarm and activate a buzzer on the device to let the wearer know that a carer had been called. This device also acted as a monitor, transmitting log messages when an impact-only event or a fall with the person immediately getting up again occurred. A commercial model was developed in which the lying time before the alarm was transmitted was reduced to 15 seconds and a panic alarm button added (Tunstall Telecom, 2000; Doughty et al., 2000).

Since then, many other wearable fall detectors have entered the market, and some of them are listed in Table 1.7. Detailed technical information about their operation is rarely published, but examination of the devices, manufacturers' literature and discussions with sales staff show that they either use tilt or a kinematic acceleration algorithm; sometimes supplemented by other kinematic sensors or sensitive barometric sensors for altitude change.

Charles Lord and David Colvin may have been the first to propose using accelerometers to measure falls in elderly people, in the late 1980s. These were not intended for alarms but to gather information about the incidence and severity of falls as a privacy-friendly alternative to video recording. They used accelerometers on mannequins in simulated falls and proposed distributing acceleration "dosimeters" which would log the times and magnitude of falls to find out the characteristics of real falls (Lord and Colvin, 1991).

It was not until the 1990s with the development of tiny, cheap, low powered accelerometers intended for automotive air-bag and seat-belt tensioning systems (Eddy and Sparks, 1998) that accelerometer based fall detectors really became practical. These accelerometers use microscopic cantilevers which are deflected by the acceleration and the degree of deflection is measured by the capacitance between the cantilever and the substrate layer below it.

The fall signature is typically a large acceleration corresponding to impact followed by constant gravitational acceleration for a few seconds as the person lies motionless (Possum Telecare, 2011; Telecom Design, 2011a). The devices usually warn of an impending alarm by vibrating for several seconds, which the user can cancel by pressing a button or, for wrist-worn devices, waving or raising their arm. Some devices incorporate additional sensors, for example the Tynetec and Philips Lifeline ones have sensitive air pressure sensors to assist the fall discrimination process (Tynetec, 2012; Philips Lifeline, 2010).

The wrist is not ideal for accelerometer-based fall detection since arm movements can produce acceleration signatures which mimic those that would be seen at the wrist from whole body movements, and the wrist has even been described as unsatisfactory, at least for simple

Name	Placement	Mechanism
Bosch Security Systems Fall detector (Bosch Security Systems, 2012)	Wrist	Accelerometer
Chubb Community Care FG158149 Fall Detector (Wrist Worn) (Chubb Community Care, 2013) (Telecom Design, 2011b)	Wrist	Accelerometers
Chubb Community Care Verso 70 degree fall detector (Chubb Community Care, 2012)	Neck	Tilt
Halo Monitoring Systems myHalo Fall detector (Halo Monitoring, Inc, 2010)	Waist or chest	Accelerometer
Philips Lifeline with AutoAlert (Philips, 2011; Philips Lifeline, 2010)	Neck	Accelerometer, barometric sensor
Possum Fall detector (Possum Telecare, 2011)	Wrist	Accelerometer
Skyguard GEMShield (Skyguard Ltd, 2010)	Neck or waist	Acceleration followed by impact
Tynetec Fall detector (Tynetec, 2012)	Waist or neck	Accelerometer
Tynetec Wrist Worn Fall detector (Tynetec, 2012, 2015)	Wrist or waist	Accelerometer, pressure sensing
Tunstall Telecom Fall detector (Tunstall Telecom, 2008)	At or above waist	Impact followed by lying on side for 15 seconds
Visionic MCT-241 PowerCode Fall Detector (Visonic, 2013)	Neck cord or waist	Tilt $>$ 60 degrees for a minute
VitalBase Fall Detector (Telecom Design, 2011a)	Wrist	Accelerometers

Table 1.7: Some commercial wearable fall detectors.

algorithms (Kangas et al., 2008). However, this location is a preferred one from the perspective of wearers, probably because of the convenience of wearing the device whilst still being capable of providing usable results and the ease with which an impending alarm can be cancelled.

These devices generally operate by following the pattern described for the experimental wrist-worn Speedy detector (Degen et al., 2003) which used an accelerometer to look for a period of near free fall followed by rapid upwards acceleration as the wearer hit the ground, and then a period of little movement whilst the person lay on the ground recovering. For this last phase the Speedy device looked for 40 seconds of inactivity in the 60 seconds following the fall. As with the earlier detectors, there is a period during this phase in which the person could cancel the impending alarm. The acceleration profile during a fall is similar to that of a waist-mounted device, as shown in Figure 1-1 on page 40, but is more prone to variation and false alarms because of the greater movement possible at the wrist than the waist.

1.4.1.3 Third generation systems

Third generation fall detection systems attempt to do much more than reactively raise an alarm after a fall, by proactively providing an early warning of increased falls risk (Ward, 2012).

This requires a sophisticated ambient monitoring system which can both raise an alarm when a fall occurs, and also alert carers to gradual deterioration or other incipient problems. For example, if the amount of movement during the day gradually declines over several weeks then this could indicate worsening mobility problems and allow these to be addressed before a fall happens.

In practice these systems potentially offer so much greater capability than just fall prevention that they are rarely targetted specifically at falls. However, converting that potential to reality is a difficult and complex problem and although there has been considerable progress since research started nearly twenty years ago (Kidd et al., 1999), there is still no clear understanding of how best to do it (Brownsell et al., 2011a).

There are few integrated systems on the market, and these require manual interpretation of sensor data. These systems, such as Alarm.com Wellness (Alarm.com, 2015), Canary (Canary Care Limited, 2015) and Healthsense (Healthsense, 2015) provide information about movement related events such as motion sensor and light activations, opening of external doors, and alerts about bouts of activity during the night or inactivity during the day. Most systems are based around changes in activity level to alert carers to problems rather than more sophisticated inferences about well-being (Brownsell et al., 2011b).

There are several reasons for the difficulty in constructing reliable automated third generation systems. Providing enough detail to track someone's well-being accurately requires many sensors, but usable systems are constrained by cost and practicality. A complex system may require motion sensors, chair and bed occupancy sensors, sensors on doors, and electricity and water monitoring. These often do not directly measure a characteristic of interest which must instead be inferred from data relying upon sometimes doubtful assumptions (Martin et al., 2006). For example, a refrigerator door sensor does not indicate whether food was removed and heavy objects activate some pressure-based bed occupancy sensors (Martin et al., 2006).

If inferring what activities from raw sensor data was not hard enough, people do not follow rigid patterns and deducing well-being from their behaviour is a challenge. For example, Martin et al. (2006) found that their system was confused into concluding that a visitor was present when the resident cleaned their flat since the rapid movement between rooms caused multiple door sensor triggers.

1.4.1.4 Conclusion

There are a wide range of commercial systems on the market. Most are systems which use a manually activated alarm. The problems of wearers being unwilling, or unable, to activate the alarms has led to the development and marketing of devices which automatically do so when they detect a fall. In the longer term these may be replaced with much more sophisticated automated systems which proactively monitor health. However, the large presence of automatically activated wearable alarms in the marketplace suggests that these offer best prospect for automated fall detection over the next few years for people with dementia.

1.4.2 Experimental fall detectors

The previous section largely dealt with commercial offerings. A great deal of research effort has been expended on automatic fall detection over the past two decades motivated by the limitations of PERS systems and the difficulty of making a reliable automatic system. There are many reviews of the intricacies of the problem and the strategies and techniques being used to seek its solution, for example, Pannurat et al. (2014); Mubashir et al. (2012); Ward (2012); Mubashir (2011); Hijaz et al. (2010); Abbate et al. (2010).

There are two broad approaches, which have been briefly described already (Pannurat et al., 2014):

- Wearable devices, which usually use accelerometers; sometimes in conjunction with other kinematic sensors such as gyroscopes.
- Fixed sensors installed in the building. These are typically either video imaging systems, or non-imaging systems which use vibration or acoustic sensors sometimes supplemented with other sensors.

Each offers different benefits and drawbacks – wearable sensors are cheaper than the building installations and can operate outside of the home, which may be important since a quarter of falls by men are in the garden (Masud and Morris, 2001). They can also monitor physiological parameters such as heart rate. But they have serious drawbacks (Chen et al., 2011b, who compared them for activity recognition, but the comments are equally applicable to fall detection) – they don't provide the "big picture" since they only sense limited data about the wearer's movements and do not see the environment that the person is interacting with (Igual et al., 2013). They must be small, comfortable and with a reasonable battery life and can only be worn on a limited range of body locations to be acceptable. The user must choose to wear them despite any discomfort or stigma and always remember to do so.

Although ambient sensors are common in assisted living alarm generation applications, such as fire, gas, flood and extreme temperature sensors (Tunstall Telecom, 2012) there are few commercially available ambient fall detectors. The greatest advantage of them over wearable devices are that they do not require the user to actively put the device on, and they provide a greater range and amount of data and consequently should be more reliable. However, imaging systems are expensive to install because of the limited view of the cameras (Hijaz et al., 2010) and risk rejection because of privacy concerns (Fleck and Strasser, 2008). Some ambient systems detect falls through inactivity, for example Canary (Canary Care Limited, 2015), or use direct video surveillance by the carer to find problems (Lorex., 2015).

Occasionally systems utilising both wearable and ambient sensors are described, for example Kepski et al. (2012) combined wearable accelerometer/gyroscope sensors with a depth camera, although it is unclear whether any improved reliability outweighs the combined disadvantages of each approach. One system which claims to be considerably more reliable is the Vigi'Fall system (Bloch, 2011) available commercially since November 2012. This uses an accelerometer attached to the thorax by an adhesive patch combined with wall mounted infrared sensors which are used to detect absence of movement following a possible fall event.

1.4.3 Experimental ambient fall detectors

Ambient sensors are more complicated to install than wearable devices, only work in a fixed location and are often sensitive to environmental variations such as ambient light levels. Camera-based video systems also have privacy issues which limit user acceptance.

On the other hand they have significant benefits. They are less stigmatizing, the user doesn't have to remember to wear them - something that might be particularly difficult for dementia sufferers - and they do not have the size and power consumption constraints of wearable devices. Finally, they can look at the entirety of the person and their environment rather than being restricted to very limited data measured at one or two locations on the person's body.

Video systems are widely researched, driven by the low cost of cameras, the advanced state of video processing, the range of data available from a single sensor and the interest in video systems amongst the artificial intelligence community. There are several reviews specifically of experimental video systems (Cardinaux et al., 2011; Kolovou and Maglogiannis, 2010). There are acceptability problems with video systems since no one likes being watched at home (Marquis-Faulkes et al., 2005), but one approach to privacy is to carry out feature extraction inside the camera unit so that its output is not an image, for example in a stereo camera system described by Belbachir et al. (2010).

Common video processing techniques (Abbate et al., 2010) include tracking the person's head (because it is large and easy to identify), looking at the body posture and looking for inactivity, or combinations of these (Chen et al., 2010). Another technique, described by Doulamis (2010) is to identify the trajectory of a person as they fall. Stereo or multiple cameras can be used to obtain depth information to form a more 3-D representation, but an easier way is to use depth cameras (Leone et al., 2011).

Depth cameras provide range information about different objects in their field of view as well as the 2-D image of a conventional camera. There are several techniques which can be used in conjunction with infrared illumination, such as time-of-flight measurements or the distance-dependent distortion of a fixed spacial pattern of dots (Langmann et al., 2012). In 2010 Microsoft released the Kinect for the games market, which was an order of magnitude cheaper than its competitors and with software capable of picking out human skeletal features from the scene. Studies have used the device both for fall detection (Rougier et al., 2011) and also to monitor gait for falls risk assessment (Stone and Skubic, 2011).

Infrared cameras coupled with acoustic triangulation have been tried (Guettari et al., 2010). Infrared cameras on their own can also be used in place of optical imaging, or with for example floor pressure sensors (Tzeng et al., 2010).

Non-video systems often use vibration or acoustic sensors (Werner et al., 2011; Li et al., 2012b; Kolovou and Maglogiannis, 2010; Popescu et al., 2008), although many other techniques have been tried such as 16×16 pixel infrared sensors (Sixsmith and Johnson, 2005), electrostatic field disturbance (Rimminen et al., 2010) and Doppler radar (Liang et al., 2011). Combinations of sensors are sometimes used, for example Ariani et al. (2010) described a system of passive infrared sensors looking for inactivity backed up by pressure mats to sense if the person is sitting on a chair or has left the instrumented area.

Several pressure sensitive floor surfaces have also been used, such as one incorporating capacitive pressure sensors (Escudero et al., 2010). A practical problem with this approach is that outside of an institutional setting installation may be prohibitively expensive and disruptive.

Whilst ambient systems may eventually become the dominant commercial fall detection technology this is far from true today, and so the focus of this thesis is on wearable devices because these are the basis for the overwhelming majority of systems currently sold and in use, and so improvements in these offer the prospect of greater short term benefits.

1.4.4 Experimental wearable fall detectors

There have been over 100 different experimental wearable fall detectors described in papers published over the last few years (see Schwickert et al. (2013) for a systematic review). These typically use a single triaxial accelerometer at a specific site or multiple accelerometers distributed around the body, which may be incorporated into wearable items such as a waistcoat (Bourke et al., 2008a), shoes (Sim et al., 2011), a hearing aid housing (Lindemann et al., 2005) and even glued onto the skin (Narasimhan, 2012). Niazmand et al. (2010) described a fall detector built into a pullover with the electronics contained in washable boxes and the wiring run along seams with a removable battery. The garment survived a washing machine before it was used, but making electronics incorporated into clothing resilient enough for the normal wear and tear of life without making the packaging too cumbersome is a considerable challenge.

Fall detection sensors have to be worn on specific parts of the body since the accelerations, and thus algorithms and their effectiveness in different scenarios, vary with location (Gjoreski et al., 2011; Aziz and Robinovitch, 2011). Common locations in experimental work are the waist, chest, thigh, sacrum, head or ankle. The waist is considered one of the best locations for an accelerometer-based fall detector and waist plus ankle is even better because it allows posture to be more accurately inferred, particularly sitting on a chair (Gjoreski et al., 2011; Abbate et al., 2011).

An evaluation of an accelerometer positioned at the lower back for measuring gait and posture is described by Dijkstra et al. (2010). It could reliably detect walking and lying down, but was less reliable for shuffling and worse still for detecting standing up and sitting down. Weiss et al. (2010) looked at using this technology as part of a fall prevention strategy, and reported using accelerometers to detect near falls in volunteers on a treadmill.

As far as algorithms are concerned most systems use fixed accelerometer thresholds, either for a single device (for example Nguyen et al., 2009) or a combination of sensors (Jacob et al., 2011), some use multiple sensors to allow posture to be determined and thresholds adjusted accordingly, and a few use machine learning techniques to modify the thresholds (Luštrek et al., 2009; Ojetola et al., 2011).

Posture can often be determined by looking at the direction of gravitational acceleration, for example a chest or waist mounted accelerometer will show caudal acceleration if the person is sitting or standing, and dorsal acceleration if they are lying on their back.

Acceleration is also a useful way of looking at a fall because a major characteristic of a fall is how the person's velocity in different planes changes. An accelerometer measures both the effects of gravity, static acceleration, and the rate of change in velocity of the device, dynamic acceleration.

A typical algorithm for an experimental accelerometer-based waist-mounted fall detector, is described by Chen et al. (2005), and looks for a high acceleration impact and an orientation change in the fall detector. The orientation is determined by looking for the static 1g acceleration due to gravity. Bagalà et al. (2012) found it to have a specificity of 94% and sensitivity of 76% when tested against accelerometer recordings of 29 real world falls.

1. Look for impact, absolute magnitude of acceleration >3g.
2. Estimate detector orientation 1 second before impact.
3. Estimate detector orientation 2 seconds after impact.
4. If there has been a change in orientation, then signal a fall

Other approaches include looking for a high horizontal velocity to exclude sitting and standing by integrating the acceleration (Chen et al., 2010) and inferring the start of a fall by integrating vertical acceleration, after compensating for gravity, to calculate velocity (Noury et al., 2007). If the peak downwards velocity exceeds a threshold value then this can be used to discriminate between deliberately sitting or lying down and falling, since a deliberate movement might be expected to happen with a lower velocity than an uncontrolled one. However, the best value for this threshold varies from person to person so calibration or automated learning is needed.

A fall can also be divided into several phases and the hardware can detect a signature for each. Figure 1-1 shows typical phases using data from a waist-mounted accelerometer on the author falling onto a mattress. These phases were first described by Degen et al. (2003) for a wrist-mounted accelerometer which looked for a signature of each phase, and are broadly similar in a waist-mounted accelerometer.

1. Phase 1 is the fall itself, in which the person is descending to the ground and the accelerometer experiences a force of less than 1g. The detector can also integrate the accelerometer output to produce velocity estimates – in this case it will infer rapid movement towards the ground.
2. Phase 2 is the impact and in Figure 1-1 a peak acceleration of 3g is seen as the mattress pushed upwards resisting the descent of the person, followed by the rebound where the mattress oscillated dissipating the remaining kinetic energy of the fall.
3. Phase 3 is the period when the person is psychologically recovering from the shock and surprise of the fall. During this period they lie still for at least several seconds. If they are seriously injured or unconscious then they may not move at all for minutes.

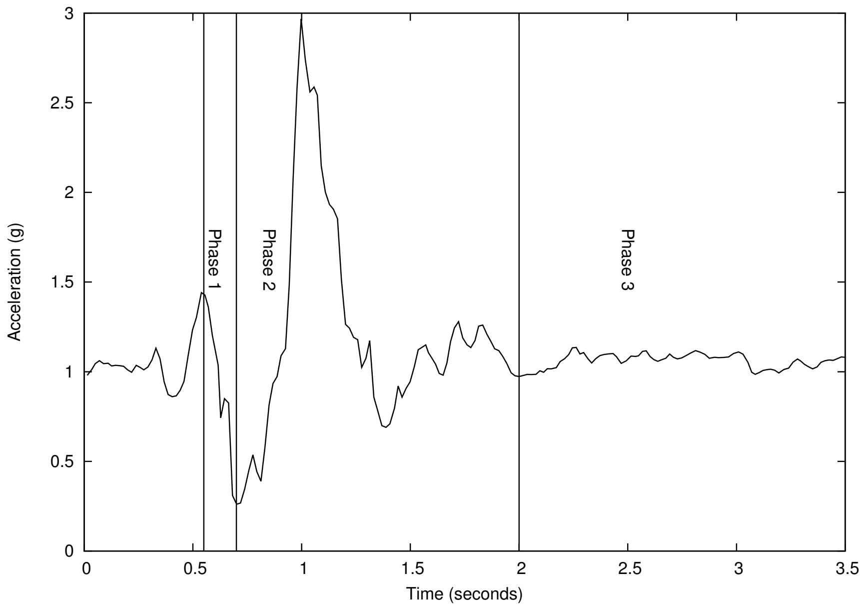


Figure 1-1: Total acceleration during a simulated fall by the author onto a mattress, measured using a waist-mounted accelerometer (phases are adapted from Degen et al., 2003)

The reliability of accelerometers for fall detection can be improved by adding other sensors, often gyroscopes for measuring angular velocity, and several researchers, and more recently commercial devices, have used sensitive microelectromechanical barometers to look at changes in altitude (Salomon et al., 2010; Bianchi et al., 2010; Tolkiehn et al., 2011). One of the big problems with fall detection is that falls can happen slowly, perhaps even more slowly than normal events such as sitting or lying down. For example, someone may slip off of a chair after fainting (Gams and Dovgan, 2011), or slow down a fall by grabbing furniture (Luštrek et al., 2011) and detecting these events using thresholds is very unreliable.

1.4.4.1 Other wearable devices containing accelerometers

There are now many wearable devices available for activity and sleep monitoring which, like fall detectors, contain accelerometers. ActivPAL (Godfrey et al., 2007) is a commercial accelerometer based activity monitor which is attached to the front of a thigh. Several versions are available (PAL Technologies Ltd, 2010) with the most functional having a triaxial accelerometer sampled at 20 Hz and with a battery life of 10 days between recharges. Since it measures leg motion, it provides information about ambulatory activity. Other devices range from sophisticated devices such as the Fitbit Charge HR featuring an accelerometer, altimeter and heart rate monitor (Fitbit, 2015) through to simple pedometers containing a weight-activated microswitch to count jolts corresponding to steps. The Fitbit device also functions as a sleep tracker, with lack of movement indicating that the wearer is asleep, and dedicated sleep monitoring devices such as the WakeMate (Perfect Third, Inc, 2011) and the Beddit Sleep Monitor (Beddit Ltd, 2014) also use accelerometers. Wrist-mounted accelerometers have also been proposed for detecting seizures (Burchfield and Venkatesan, 2007), and in the form of an extensive set of sensors for tracking upper limb position (Hyde et al., 2008).

1.4.4.2 Smart phones as fall detectors

Smart phones contain accelerometers, and their widespread use makes them attractive to consider for fall detection. Several Android phone applications have been developed for detecting falls (Dai et al., 2010a,b; Sposaro and Tyson, 2009), for measuring gait (Hynes et al., 2010), and for monitoring movements such as standing up and sitting down (Bieber et al., 2010). A drawback of fall detection using a phone is that within the home the person must carry it on their body at all times, and outside it needs to be in a pocket rather than a handbag. Unfortunately mobile phones often do not adequately cater for the impaired vision, hearing or manual dexterity which elderly people can have (Pedlow et al., 2010) and have other potential problems such as poor battery life, which means frequent recharging and an inability to carry out continuous monitoring if it causes high power consumption, along with uncertain acceptance by users of this approach (Igual et al., 2013). However, a smart phone in a handbag might have a less direct, but still important, role in automatic fall detection by providing a telecommunications gateway and location information after a fall detected by a separate device (Lee and Carlisle, 2011).

1.4.4.3 Location-based systems

One novel non-accelerometer technique used radio location devices attached to the chest, and optionally the waist and ankles. The Confidence system is a prototype system which provides sufficient body position data to allow the person's activities to be recognised so that deterioration can be detected as well as fall detection (Luštrek et al., 2009). However, since the limb position data was accurate Luštrek et al. (2011) claimed that it was better than accelerometer-based techniques at reliably detecting falls, and found that adding location data to accelerometer based fall detection greatly increased reliability for fall detection.

1.4.4.4 Pre-impact detectors

A few researchers have built prototype pre-impact detectors so that hip protector airbags or other active devices can be deployed before the person hits the ground. This is difficult because the fall signature is limited to the pre-impact phase, and so these systems often use more sensors than fall detectors to compensate, for example complete inertial measurement units (Shi et al., 2009) or multiple sensors distributed along the trunk and leg (Nyan et al., 2008). Techniques are usually based on looking for high vertical velocities by integrating accelerometer output. Wu and Xue (2008) used waist-mounted accelerometers and found peak vertical velocities of more than $3\,\mathrm{m\,s^{-1}}$ during falls from as low as 61 cm, compared to $1\,\mathrm{m\,s^{-1}}$ for normal daily living events.

1.5 Summary

As population sizes increase and people live longer, the numbers who suffer from diseases linked to old age also increases. Diseases which cause serious cognitive decline are vastly more common in the elderly population than in younger people. At the same time injury through falls is much more prevalent, both because the elderly are more fragile than younger people and because falls are more common for a variety of reasons. Dementia itself doubles the likelihood of having a fall.

Many interventions can help reduce the likelihood of falls, although they are less effective for people with dementia. Falls will never be eliminated and if someone is injured in a fall it is essential that assistance is provided quickly. There are electronic devices available which can do this, of which the overwhelming majority are wearable.

However, they are of sufficiently doubtful efficiency at detecting falls that the wearer is responsible for cancelling false alarms. This is a difficult task for many people with moderate dementia because they may lack an understanding of the device and the warning alarm. A better fall detector is needed for these individuals, which produces virtually no false alarms but successfully detects all falls. Since there is no agreement about what a fall is, it is also necessary to consider what definition needs to be used. However, addressing this is not enough on its own, since the cognitive effects of the most common forms of dementia make a wearable device less acceptable.

Despite their defects, it is likely that wearable fall detectors, however imperfect, will continue to be commercially dominant for fall detection because of their established position in the marketplace.

The approach taken in this thesis is to find ways of improving fall detectors to mitigate both the effects of falls and the worry felt by carers. The question it examines is “How can a reliable wearable fall detector be constructed for people with moderate to severe dementia?”

Chapter 2

Making a better fall detector

This section considers what might make a better wearable fall detector than currently available for people with dementia. It describes the desirable features of the detector and considers how these might be attained.

There are two main problems with the current generation of fall detectors. The first is that they do not reliably differentiate between falls and other common events which happen during normal daily living. Efficiency is a better term than reliability when discussing this because reliability can be confused with the device's propensity for electronic or mechanical failure. An important reason for the inefficiency is because testing is very imperfect, usually relying upon simulated falls by young, healthy people. Noury et al. (2008) even expressed the view that there was no satisfactory commercial fall detector available, and little has changed over the following years. The second major problem for fall detectors and other wearable alarm devices, is that they carry a stigma because they can be perceived as badges of vulnerability. This can cause wearers to avoid being seen wearing them or sometimes reject them entirely (Steele et al., 2009).

2.1 Efficiency

There are no large scale studies of the reliability of commercial fall detector at detecting falls, but there are several accounts of the false alarm rate, for example, Brownsell and Hawley (2004) described a study where they provided 34 participants with commercial waist-mounted devices and evaluated their use. 21 of the participants wore the alarms at least occasionally, and the alarms produced a false positive alarm rate of about one per user per month. However, the same study reported three cases where a genuine fall was not correctly detected and only one fall where the device generated an alarm, although one of the false negatives may have produced an alarm it had been cancelled by the wearer by mistake.

Even if this were the case, the sensitivity of the devices may have been compromised by the need to keep the false alarm rate down. Since real falls are rare with months or even years between them, the typical user is likely to be much more aware of false positives than false negatives because their opportunity to experience false negatives is so limited. Several commercial fall detectors have a small selection of sensitivity levels, but this is not really satisfactory since the sensitivity is turned down until the false positive alarm rate becomes acceptable, at the expense of reducing the likelihood of detecting a real fall.

More recently Kangas et al. (2015) evaluated a prototype waist mounted fall detector on 16 people aged 65 upwards, during which 15500 hours of data was collected. The devices detected 12 out of 15 falls where the detector was being worn and produced an average of one false alarm per 20 hours of operation. An additional three falls went undetected because the faller was not wearing the device. The false positive rate could have been reduced to one per 40 hours with two algorithm changes. Ignoring data recorded during the first and last fifteen minutes of each usage period reduced the false alarm rate by 40% because many false alarms were generated when a participant put the device on or removed it. Amalgamating multiple alarms recorded within a minute of each other reduced false alarms by a further 10%.

Bourke et al. (2010b) evaluated a set of experimental waist-mounted accelerometer algorithms on data recorded from 10 elderly people performing unscripted normal daily living activities for a few hours each, and found that false positive alarms were generated by the algorithms at an estimated rate of between 0.94 and 45 per 16.5 hour day. Bourke et al. (2010a) proposed a new algorithm which produced the equivalent 0.6 false alarms per waking day when tested using normal activities of daily living dataset. One reason for the relatively low false alarm rate was the trunk tilt angle as one of the checks for detecting a fall. It has nevertheless been criticised for its inability to detect low impact falls (Bagalà et al., 2012), with a sensitivity of only 83% when tested against a library of 29 real falls.

Whilst the high false positive rate might be acceptable to many wearers, this is not reasonable for someone with moderate dementia since they may not understand the warning that an alarm is about to be generated or be unsure how to cancel it. The result of the alarm can be very disconcerting, with unexpected visits by care workers or disembodied voices from communications devices (Porter, 2003). If a false alarm is not confirmed by a call centre but passed directly onto the carer then the carer may be unnecessarily distressed and their life disrupted by the false alarms, and may eventually consider the device to be more trouble than it is worth.

2.1.1 Benchmarking and testing

One serious issue affecting reliability is the lack of standardisation for comparative trials of different fall detection devices (Noury et al., 2007), and precise recording of the relevant physical characteristics of the test subjects and the falls. Many experimental projects report impressive success rates, but it is not clear that these would be achieved outside of the artificial conditions of a laboratory.

Testing could be carried out by providing elderly people with prototype devices and evaluating their performance with the real falls that the wearers experience, which is the strategy normally used in trials of medical devices. However, a member of the general population in the age range 75–85 will only experience one fall every year or two and even people who often fall may only have three serious falls in a year. Consequently, a large number of devices and participants would be needed for adequate testing within a reasonable timescale (Klenk et al., 2011).

The EU-funded Farseeing Project is building a database of accelerometer data, with around 200 real-world falls, and has defined a standard format for collecting the data (Becker et al., 2012). Some researchers have used data collected from sufferers of progressive supranuclear palsy (PSP), a disease where falls are common since it causes serious gait and balance problems. For example, the EU SensAction-AAL project collected lower back-mounted accelerometer data from 32 falls, the majority from PSP sufferers and used it, along with ADL activity data, to evaluate fall detection algorithms (Palmerini et al., 2015; Bagalà et al., 2012), and Kangas et al. (2011) utilised data from five falls by PSP sufferers.

The earliest fall detectors were tested with a jointed mannequin (Doughty et al., 2000) and dummies are still occasionally used (e.g. Zhang et al., 2006). However, most testing uses young, healthy volunteers deliberately falling onto a padded surface, and sometimes copying video of an older person falling (Bourke et al., 2010a; Boyle and Karunanithi, 2008). Unfortunately, fall detectors which appear effective when tested in this way are less effective when tested against the small amount of real fall data available (Bagalà et al., 2012) because simulated falls tend to be unrealistic imitations of the real events:

- Younger people do not fall in the same way as older people, nor do they attempt to arrest the fall in the same way. For example, Kim and Ashton-Miller (2003) found that older people showed larger elbow movement and smaller wrist movement when stopping forward falls with their hands. In some work, participants try to mimic real falls in elderly people (Aziz and Robinovitch, 2011), and although it seems a good approach the real effectiveness is debatable.

- A deliberate fall does not mirror an accidental one because the person has both conscious warning and unconscious anticipation and likely to act differently, for example making small postural adjustments just before the simulated fall (Becker et al., 2012).

- A fall onto a padded surface does not mimic a fall onto a hard surface because the impact and deceleration forces are lower (Becker et al., 2012). Even then the person will normally land benignly, for example to avoid hitting their head.
- All falls are unique which means that numerous scenarios need to be specified and tested to provide representative coverage.

Outside of fall detection, several researchers have utilised uncontrolled falls which are arrested at an early stage, for example Roos et al. (2008) tripped subjects walking on a treadmill, arresting the fall with a safety harness; and for EMG studies of the startle response Bisdorff et al. (1999) allowed a tilt table to fall from a 10° head up angle to horizontal where the motion was arrested by rubber bungees. However for evaluating fall detectors, the only strategies currently available are to use the small amount of data collected from real falls, or accept the serious limitations of simulated falls.

2.1.2 Algorithms and modelling

Fall detection algorithms are usually developed using simulated falls by young, healthy volunteers for the very sensible reason that using frail elderly people risks serious injury. Boyle and Karunanithi (2008) intended using real data collected from stroke rehabilitation inpatients to develop algorithms for a bi-axial accelerometer based fall detector, but abandoned this after collecting accelerometer profiles for only four falls in 309 days worth of data.

Most papers describing fall detectors use an ad hoc list of falls and non-fall events. Abbate et al. (2010) proposed a set of twenty different types of falls, as shown in Table 2.1, which should be detected during fall detector evaluation and sixteen non-fall events (Table 2.2), which should not. They also suggested that these could be linked together during testing into a sequence of events called *circuits*.

Bagalà et al. (2012) used data from a triaxial accelerometer mounted on the lower back from 29 real falls, largely by people with progressive supranuclear palsy, to re-evaluate 13 published algorithms and found that their performance on real world falls was much worse than on the simulated falls that the algorithms had originally been tested on.

Even when an algorithm is tested against the small amount of data collected for real falls it may not reflect the true performance of the fall detector, because of the actual physical characteristics of the device rather than the idealised characteristics from modelling. It might be feasible to use an industrial robot arm to produce the accelerations to simulate real falls in a repeatable and rigorous fashion. The arm would describe an arc in which the acceleration was carefully controlled and an accelerometer-based sensor might then see identical accelerations to those recorded in the real fall.

Fall direction	Name (Abbate et al., 2010)	Description
Forwards	"Front-lying"	Fall forwards
	"Front-protecting-lying"	Front-lying with arm protecting faller
	"Front-knees"	Falling onto knees
	"Front-knees-lying"	Front-knees then fall forwards
	"Front-right"	Fall forwards, ending on right side
	"Front-left"	Fall forwards, ending on left side
	"Front-quick-recovery"	Front-lying with fast stand up
	"Front-slow recovery"	Front-lying with slow stand up
Backwards	"Back-sitting"	Backwards fall to sitting on floor
	"Back-lying"	End lying on back
	"Back-right"	End lying on right side
	"Back-left"	End lying on left side
Sideways	"Right-sideway"	Fall onto right side
	"Right-recovery"	Right-sideway plus standing up
	"Left-sideway"	Fall onto left side
	"Left-recovery"	Left-sideway plus standing up
Vertical	"Syncope"	Vertical collapse
	"Syncope-wall"	Sliding vertically down wall
Miscellaneous	"Podium"	Vertical fall to ground from elevated podium
	"Rolling-out-of-bed"	Rolling from bed onto floor

Table 2.1: The different types of simulated falls proposed by Abbate et al. (2010) for evaluating fall detectors and fall detector algorithms. A fall detector should reliably detect all of these.

Probably the most important outcome of testing any fall detector algorithm is an understanding of how it would perform in practical terms, what proportion of falls would be detected, and what the false alarm rate would be, and this is the subject of the next section.

2.1.3 Sensitivity and specificity

Fall detector efficiency is often quoted in terms of sensitivity and specificity, for example by Kangas et al. (2009), Bagalà et al. (2012), Boyle and Karunanithi (2008), Lindemann et al. (2005) and Jacob et al. (2011), measures which are normally used to characterise the efficiency of clinical diagnostic tests. Typical quoted values for fall sensitivity are $\approx 97\%$ and specificity $\approx 100\%$, for example in Chen et al. (2011a).

The usual method is to test the detector (or the algorithm it uses) against a set simulated falls and a set of non-fall events which could be misidentified as falls. The specificity is the measure of the proportion of true falls detected and the sensitivity the proportion of non-fall events correctly rejected.

Type	Name (Abbate et al., 2010)	Explanation
Lying	"Lying-bed" "Rising-bed" "Sit-bed"	Sideways motion from standing to lying on couch Sideways motion from lying on couch to sitting on edge From sitting on a yielding mattress to lying on back
Sitting	"Sit-chair" "Sit-sofa" "Sit-air"	Sitting on a rigid chair seat Sitting on an upholstered chair seat Sitting pose without surface
Moving	"Walking" "Jogging" "Running"	
Bending	"Bending" "Bending-pick-up"	Bending forwards Bending to pick object from ground
Miscellaneous	"Stumble" "Limp" "Squatting-down" "Trip-over" "Coughing-sneezing"	Walking stumble and recovery Walking with a limp Squat and stand Bending and recovery whilst walking

Table 2.2: Non-fall events which should tested during fall detector evaluation (Abbate et al., 2010)

$$\text{sensitivity} = \frac{\text{True positives}}{\text{True positives +False negatives}} \qquad \text{specificity} = \frac{\text{True negatives}}{\text{True negatives + False positives}}$$

There is usually a balance to be struck between sensitivity and specificity, and algorithms can be tuned to increase one at the expense of the other.

However, it is worthwhile considering what these measures really mean to the wearer of a fall detector, because there is an important difference between a medical test and an algorithm implemented in a fall detector. A medical test is carried out once to determine whether the condition exists at the time that the test takes place, whilst a fall detector is continuously repeating a test. This has implications for the specificity measurement because every time that the test is performed there is a probability that a false positive will be generated.

For a fall detector the sensitivity is useful because it represents the proportion of falls that would actually be detected, for example a sensitivity of 90% means that nine out of ten falls are detected. This is meaningful information which can be used to inform a judgement of the device's effectiveness.

However, the specificity is far less useful because whilst it provides a relative measure against which fall detector algorithms can be compared it does not provide any indication of the false alarm rate that would actually be observed by the wearer. If the "fall detection" test is repeated numerous times over a short period then even one with a good specificity might be expected to produce many false positives, and so a clinically acceptable specificity would result in a stream of false positives. Bagalà et al. (2012) pointed out that a fall detector producing one fall/no-fall result every minute with a specificity of 96% – excellent for a diagnostic medical test – would generate two false alarms an hour.

Furthermore, detector algorithms are better at correctly discounting some types of non-fall events than others because some have greater peak accelerations than others. For example walking is a more common event than sitting down on a chair, but during testing each type of non-fall event is typically repeated the same number of times and given equal weight to all other non-fall events. No test that the author has seen weights different non-fall events by likelihood. Two fall detectors with the same specificity may have differing actual performance depending upon the frequency of the different events they are prone to mis-categorise as falls. A fall detector which had a 1% probability of generating a false positive whenever a person sat down would be worse than one which instead had a 1% probability of a false alarm whenever the individual bent down to pick something up from the ground even though they show the same specificity under the same test conditions.

Rather than specificity, the best measure for practical purposes is probably how many false alarms will the fall detector produce in a given time period. For this to be determined through testing by simulated non-fall events requires an estimate of the rate at which the different non-fall events occur so that these can be linked to the observed false positive alarm probability for a fall stemming from of each of these individually.

2.2 Acceptability

A personal alarm device can be seen as a humiliating badge of vulnerability or inadequacy (Steele et al., 2009). Some people would not want it known that they had fallen except when they have tried, and failed, to get up themselves (Brownsell et al., 2000). Wearers may be also be concerned about false alarms resulting in embarrassment if a carer attends (Brownsell et al., 2000).

Even those that do elect to wear these devices usually only do so for part of the day, as one study of the users of a particular model of PERS found. 87% of nearly 1500 respondents said that they wore it always or mostly around the home, but only 30% wore it in bed and 46% in the shower or bath (De San Miguel and Lewin, 2008). The reasons for not wearing the device in bed were that the neck cord might get twisted and fear of inadvertently setting the alarm off, whilst in the shower or bath they were the physical discomfort because the neck cord got wet, and fear that water would damage the device – even though many had been told that it was waterproof. Failing to wear the device in these situations is a concern since a wet floor in a bathroom can make it a high risk area for falls, and many people climb out of bed to visit the toilet several times during the night. Sometimes people choose not to wear assistive living devices simply as an expression of their own free will (Steele et al., 2009).

> "I can choose to wear it or not wear it [hearing-aid] and when I want to rebel, I'll just say "I don't think I'm going to wear it today!" and I won't wear it."
>
> (Focus group participant quoted in Steele et al., 2009)

Wearers' reactions are not all negative, however, in a study of 55 people who wore waist-mounted fall detectors, Brownsell and Hawley (2004) found that 90% were pleased they had it, although this is an unsurprising statistic given that the group selected were people who were currently using the devices and did not include people who had tried and abandoned them.

Researchers have asked prospective users about most acceptable forms for wearable devices. Mahoney and Mahoney (2010) found in a small sample of 9 people with Alzheimer's disease that the most acceptable format for a wearable wander tracking device was a wrist or ankle band, or a brooch. Not surprisingly a systematic review of body worn sensors, including fall detectors, found that most people prefer devices which are small, non-invasive and do not affect their normal activities, and they disliked devices which labelled them as vulnerable (Bergmann and McGregor, 2011). Also, they prefer discrete devices integrated into normal clothing or accessories rather than a separate device. A questionnaire study of elderly people suggested that a heart rate monitoring device strapped to the wrist is better than one requiring a chest band, although one of the respondents pointed out that it has to be removed for washing up (Holzinger et al., 2010).

Mahoney and Mahoney (2010) highlighted other strategies which can reduce the likelihood of the device being removed, including using an ankle band which is less accessible than a wrist band, incorporating the device into clothing, or making it appear to be an item of jewellery, although it still needs to be recognisable to first responders as a monitoring device. Researchers have experimented with incorporating sensors into clothing such as a sock (Doukas and Maglogiannis, 2011), a jacket or shoes (Sim et al., 2011).

Some devices are physically difficult to remove, for example the wrist worn tagging device described by Miskelly (2004). However, making a device hard to remove or concealing it from the wearer creates ethical problems around dignity and privacy (Mahoney and Mahoney, 2010). A device which is securely fastened to a person can also cause safety problems, for example Mahoney and Mahoney (2010) described a pendant alarm with a strong neck cord which caused several serious strangulation incidents.

2.3 What would make an ideal fall detector?

Drawing on this work, the characteristics of an idealised wearable fall detector for someone with dementia are shown in Table 2.3. Of these, the efficiency in detecting falls and rejecting non-falls, for example sitting heavily in a chair, and improved acceptability are the most important because these are the ones which are both the most often expressed as the cause of concern, and are the subjects of practically all academic papers on fall detection. The ideal wearable fall detector is likely to still be built around an accelerometer because uncontrolled acceleration and deceleration is a defining characteristic of a fall.

Small and unobtrusive
Physically attractive, possibly disguised as a bracelet, brooch or watch
Reliable in detecting the falls which cause distress
Easy to put on
Not generate an alarm for in response to events which were not real falls
Require infrequent maintenance, for example a long battery life
Comfortable to wear
Waterproof
Rugged, not damaged by being dropped, or cause injury to faller
Inexpensive
Be easy to use, ideally without any training
Have an interface for the carer which was appropriate for their needs and abilities

Table 2.3: Characteristics of an ideal second generation fall detector (synthesised from Bergmann and McGregor, 2011; Holliday, 2012; HDTI, 2012; Ward, 2012; Doughty et al., 2000)

However, an accelerometer on its own may be insufficient to discriminate between real falls and other events. There are several reasons for this. The first is that despite a considerable amount of research it has proved impossible to produce anything approaching a perfectly reliable accelerometer algorithm, and even if this could be done different fallers have different characteristics. One of the difficulties is that falls can be very gentle without high peak accelerations. A second difficulty is that a fall is defined as more than a kinematic event. As Section 1.3.4 describes, different groups have different definitions of a fall which are often based on the reason that the fall is relevant to them, so the design of an ideal device needs to take into account the reason for wanting to detect the fall. Two events may be practically identical kinematically but if one is controlled and the other not, or one results in injury and the other not, then only one will be a fall.

A combination of techniques is probably necessary – given the difficulty of the problem there is probably no silver bullet, no single algorithm or sensor, which is capable of producing flawless fall detection. It may require a combination of kinematic, physiological and environmental sensors.

An ideal device would be worn at all time, even at night time as the wearer may get up to visit the toilet or kitchen and fall. The waist is a good site kinematically but not an ergonomically ideal site since this would require a belt to be constantly worn (although some people in Kangas et al. (2015) did wear the belt-mounted sensor in bed). Ergonomically the wrist and ankle are good sites as many people are used to wearing watches or socks and so the device would not be uncomfortable or feel strange to them.

The upper arm is a possibility, but likely to be uncomfortable during the night if the person is lying on it, and can interfere with clothing. Implementing the device as a small earring might be workable, and the ear is an excellent site for physiological monitoring (He et al., 2010). However, there may be aesthetic problems and many people feel uncomfortable wearing earrings in bed.

The device could be incorporated into a hearing aid as tried by Lindemann et al. (2005), glasses or dentures but there is a risk that these would not be worn on a trip to the bathroom during the night. A very compact device could be worn as a ring or an earring, but these are too ambitious with the current levels of technology.

If the fall detector is to be mounted on the ankle or the wrist then a simple tilt sensor will not work (Doughty et al., 2000) but accelerometer based systems do at some level (Degen et al., 2003), and commercial wrist-mounted systems are widely available. The ankle has not been directly compared with the wrist as a site for a fall detector, although it has been compared with locations which are better than the wrist. For instance, one study looked at accelerometers placed at the waist, chest and thigh, as well as the ankle and compared the results from these, and found that the ankle and the thigh as a single site did not produce good results (Gjoreski et al., 2011). A single ankle sensor would be insufficient since the legs operate asymmetrically in a trip and so kinematic sensors are required on both ankles (Aziz and Robinovitch, 2011).

2.4 What additional sensors could be used?

Most researchers have focused on acceleration as a way of detecting falls, occasionally augmented by gyroscopes or other kinematic sensors, because these devices are inexpensive, and provide a clear signature of events which appear to include many falls. Although tilt and impact sensors were used in the first commercial model (Williams et al., 1998a), these are just limited forms of accelerometers. But whilst accelerometers are attractive devices to use in fall detectors, there are other types of sensors which can, and sometimes are, used to enhance them.

2.4.1 Other kinematic sensors

Additional kinematic sensors such as barometric (air pressure) sensors and microelectronic gyroscopes are often used as an adjunct to the accelerometer to provide additional data.

Barometric pressure sensors provide vertical position change information regardless of position, and have been included in some commercial fall detectors. However, the range of kinematic sensors available is limited and the technology less developed. Since a fall does not always involve rotation, a gyroscope is less useful.

One of the avenues briefly considered when planning this PhD was the examination of ankle movements following a possible fall, as the subsequent ankle movements could help discriminate between falls and non-fall events, and gyroscopes may have been key to this.

Whilst accelerometers are technically well developed, with a wide selection of reliable low power three-axis devices cheaply available, gyroscopes by comparison have poorer performance. Most gyroscopes are biaxial rather than triaxial (which was true accelerometers several years ago) and suffer from appreciable drift rates. Similarly, the author has found experimentally that inexpensive electronic air pressure sensors are very noisy when measuring over ranges of a few tens of centimetres. The noise can be reduced by averaging, but this increases the response time as multiple readings need to be taken.

2.4.2 Position and velocity

Accelerometers, gyroscopes and barometric sensors are very convenient to use in fall detectors because they operate solely by examining their own internal state and so do not require any data source external to themselves. However, an accelerometer only provides one of the three key elements of the kinematic description of an object. The two missing elements are the device's position and velocity. These require more complex sensors because, unlike acceleration, they have no meaning without an external frame of reference, and so most systems must continuously compare themselves with something fixed in the environment outside of sensor. The only technique for avoiding this is inertial navigation, maintaining a constantly updated internal software model of the reference frame, which brings its own set of problems since it requires the continuous monitoring of exquisitely accurate accelerometers and gyroscopes.

What is needed is a 3-D location system capable of several accurate position updates per second with a resolution of 1 cm or less, as this would provide velocity and acceleration data as well as position. This resolution would give velocity and acceleration resolutions of $0.01\ \mathrm{m\,s^{-1}}$ and $0.01\ \mathrm{m\,s^{-2}}$ or better. However, this spacial resolution is ambitious since practical indoor location systems are at least an order of magnitude poorer than this (Curran et al., 2009).

Luštrek et al. (2011) used a location system, with a resolution of only 15 cm, to track the movements of a person wearing one location tag on their chest, or a tag on each limb. The authors reported better results when using a single tag than with an accelerometer, and substantially better ones using four tags. As already discussed, laboratory tests of fall detectors are not necessarily representative of performance in a real environment but these results are suggestive.

Indoor location could also help fall detection, both by indicating whether the person is on the ground, and by providing context information about where the possible fall occurred. For example if an accelerometer event is seen at the location of a chair then it is likely that the person was just sitting down (Gjoreski et al., 2011).

Incidentally, Luštrek et al. (2011) suggested that a great deal of contextual information could be gathered and used to advantage, for example if the person was carrying out a high risk activity such as exercising, or checking if the possible fall event has happened at a time when falls are most likely. Whilst much of this is beyond a wearable detector, there is certainly some scope.

2.4.2.1 Indoor location

Accurate and reliable indoor location systems which might be used in a wearable fall detector are currently expensive. Global navigation satellite system (GNSS) receiver modules are cheap and almost ubiquitous for determining location outdoors, although without specialised techniques the position resolution is at best a few metres and the update interval, along with the velocity resolution of $0.1\,\mathrm{m\,s^{-1}}$, is an inadequate substitute for an accelerometer.

They also work poorly indoors, if at all, for two reasons. The already very feeble satellite signals are further attenuated passing through the fabric of the building and the multiple paths created by reflections from walls makes the receiver's task of picking out the signal from the noise even harder (Piras and Cina, 2010; Dedes and Dempster, 2005). One solution which is under development but not yet cheaply available is to use multiple GNSS transmitters inside the building, generating either a simulated signal or broadcasting signals from receivers on the roof to simulate a satellite constellation (Fluerasu et al., 2010; Ozsoy et al., 2010). It only became legal in 2012 to use GNSS repeaters in the UK because of concerns about possible interference with other users (Ofcom, 2012).

Most alternatives to GNSS which work indoors use a network of either radio or ultrasound transmitters. Generally speaking a localisation system based on fixed transmitters has three techniques available to it, based on the direction the signal arrives from, its speed, or its attenuation with distance from the transmitter (Curran et al., 2009). None of these are completely predictable, however, and there usually needs to be on-site surveying and calibration which makes them less suited to assisted living applications.

Triangulation uses the angles between the sources to determine location, and although it is the basis of traditional surveying and navigation it is unsuited to small modern systems because it relies upon directional antennae which imposes size constraints.

The most common technique is trilateration, which uses the distances to the transmitters instead of their angles, and most systems, including GNSS, exclusively use this method. As with triangulation, three transmitters are needed to locate position in 3-D, although more are desirable to reduce error limits. In most cases the transmitted signal contains a timestamp showing when it was transmitted, although some ultrasound systems use a separate radio signal to provide synchronisation, which avoids the complexity of embedding timing information in the acoustic signal.

Trilateration of mobile phone masts signals is often used in outdoor commercial systems to overcome the 30 second or so delay which GNSS systems require when they first start up, and to satisfy the US federal requirement for mobile phone operators to be able to locate emergency callers (Wang et al., 2000). However, the accuracy is tens to hundreds of metres (Curran et al., 2009) and inadequate for fall detection. Transmitters based in the home would be needed for this.

The third technique is to use the received signal strength. The simplest method is to install numerous very short range transmitters and the receiver can then determine its location from which it can see, but this is expensive. If a more powerful transmitter is used and signal strength varies predictably with distance from the transmitter then trilateration can be used, but in practice objects in the environment usually cause reflections and complicate attenuation and an empirical signal strength map must be plotted, called *fingerprinting*. Fingerprinting methods are superficially attractive because they can be cheap, for example using signals injected into the mains wiring and re-radiated (Patel et al., 2008), but producing the map represents a significant overhead. Most commercial indoor systems use the received signal strength from radio signals (typically WiFi) or even magnetic fields, but these are complex and require recalibration following any wireless network topology changes. There are also a range of RFID techniques, but accurate systems are still expensive, since they need multiple receivers or transmitters.

Whilst radio frequency (RF) system are the most common, ultrasound based ones are easier to build because the speed of sound in air is a million times slower than radio waves and so the performance required from the timing electronics is much less stringent (Sanchez et al., 2009). The Cricket system (Priyantha, 2005) used trilateration of acoustic chirps emitted by fixed acoustic sounders with RF signals transmitted simultaneously to provide timing. The RF signal arrives at the receiver practically instantly to be followed by the acoustic signal some time later. Unfortunately, ultrasound systems are prone to problems because the speed of sound in air is influenced by temperature and humidity, transducers are far from omnidirectional and other acoustic sources can interfere with the signal especially at longer ranges when it becomes attenuated (Misra et al., 2011).

A variation is to swap the position of the transmitter and receiver, and have the object to be located carrying the transmitter. This is relatively rare outside of RFID tags – an RFID transponder carried by the person is interrogated and the response time is used to trilaterate the position (Li et al., 2012c), and sometimes done with acoustic systems, for example the Active Bat system (Harter et al., 1999).

There are two other methods which do not require a network of transmitters or receivers. The first is to use image recognition, which is how people navigate around buildings. Visible images are normally used, but sonar and lidar are also possible. This technique, and the allied one of generating a visual map, are major topics in mobile robotics, where the activity is called SLAM, Simultaneous Location and Mapping (Durrant-Whyte and Bailey, 2006a,b). Using SLAM would require the wearable fall detector to be equipped with a camera, or possibly some other sensor, something that is discussed in Section 2.4.3.2.

The second technique is inertial navigation, carefully tracking the accelerations and rotations of the sensor following the accurate measurement of its location and velocity. If this is done continuously then the current velocity can be determined and location constantly updated. Aircraft have been able to navigate using this technique since the 1950s (Titterton and Weston, 2004, page 13). The development of miniaturised solid state accelerometers and gyroscopes means that integrated modules are available for around £50 but these are not yet good enough to track position accurately for more than a few minutes, although they may have a role in interpolating position between updates from other location sensors. For example Jimenez et al. (2009) found a 5% position error with a unit strapped to a shoe following a circular path of a few hundred metres. Extrapolating to a fall detection scenario, the wearer need only travel 2 metres before the position error reaches about 10 cm.

There is currently no inexpensive and accurate low power method of indoor position location but there is such a strong demand for it and so many people working in the field that inexpensive systems will probably become available over the next few years.

With sufficient accuracy a location system alone could provide velocity and perhaps acceleration too, although most systems are not capable of this since resolutions are usually no better than 10 centimetres. This type of system could be thought of as mimicking camera-based pervasive systems to some extent, since they provide good location information from which velocity and theoretically acceleration can be derived.

2.4.3 Other sensors

There are many other types of sensor apart from ones which provide kinematic information. Some plainly have little role to play, for example fluid velocity or ionising radiation, but several are much more promising.

2.4.3.1 Sound sensors

Sound is worth considering for a fall detector, since the person crying out might provide evidence of distress as a response to a fall. Emotions and mood can be deduced from characteristics of speech and so this information could be inferred from anything said. Broek (2011) found that affective state could be determined from the variability in the fundamental pitch frequency, the air pressure and the energy of speech (along with heart rate variability). There is of course a large gap between laboratory experiments and practical devices, but the sensor might only need to indicate a likelihood of anger or fear following a possible fall event. The person may be angry or afraid as a result of something other than a fall, but a characteristic accelerometer signal accompanied by a change in affective state to distress would provide strong evidence of the fall. A sophisticated detector may able to recognise particular phrases or distress sounds, and several authors (Vacher et al., 2012; Istrate et al., 2006; Fleury et al., 2008) have reported experimental ambient systems of this type.

Some people may not cry out after falling, which may be more likely if the person knows that they are alone. A major problem would be to evaluate the efficiency of the detector, and whilst a microphone may help some people it would make no difference for others.

There might be practical problems with environmental noise, for example radio or television dialogue might be mistaken for speech by the person wearing the fall detector.

2.4.3.2 Cameras

A camera provides information about the environment rather than the person, and might be incorporated into a wrist or ankle fall detector and could provide confirmation of a fall in many cases. A belt-worn system described by Casares and Ozcan (2012) looked for rapid changes in the number of edges orientated in different directions and claimed a 91% fall detection rate (and an 11% false positive rate). This type of system might be sufficiently reliable if combined with kinematic sensors. A limitation might be the visual field available to the camera, for example if it was covered by clothing. Other considerations would also be critical, the device being able to operate in the dark and not require frequent battery charging.

Adding a camera to a fall detector could also provide location information using visual navigation techniques of the type often used in robotics. This could help establish the context of a possible fall as well as help confirm whether it has taken place which might help to eliminate false alarms. However, location mapping using images is difficult and computationally expensive, and requires the system to maintain a substantial library of mapping data, perhaps by continuously constructing a map as the user moves around. On balance there are far easier, less intrusive and more reliable ways of carrying out indoor location than this.

Privacy would undoubtedly be a serious issue, even more so than for ambient camera-based fall detectors since there would be no getting away from the device, although it would also have the benefit of working wherever the wearer was and not just where there happened to be fixed cameras located.

A semi-automatic fall detection system could be envisaged where a carer receives the video stream only after other sensors in the device show a fall may have occurred and the carer can provide confirmation. This would avoid some privacy difficulties and preserve battery life, although possibly at the risk of overloading the carer with false alarms. A waist belt might be a good site technically for a camera because of its fixed field of view relative to the person.

2.4.3.3 Proximity

It would be possible to use an ultrasonic proximity sensor to get an indication of the closeness of walls, floor and the person's body to the sensor. It could conceivably provide some indication of a fall when used in conjunction with accelerometer-based fall detection, since the person is likely to be close to a wall or a floor. To the author's knowledge no experimental fall detector has been described using this type of device as an adjunct to the kinematic sensors.

The device would have to provide more information than the range of the closest object, which is all that proximity sensors normally do. It would have to indicate perhaps that there was a strong response 60 cm away, which might be the person's body, and 10 cm away, which might be the floor; and would have to provide a stream of data since the person may be moving the limb on which the fall detector was located. Directional information, with respect to the accelerometer signal, would be very useful. It could for instance indicate if the person was on the floor from the presence of a large signal in the direction of gravity, but implementing this would be technically difficult. There would be practical problems with the device, for instance it may be confused by the presence of a sleeve if worn on the wrist.

2.4.4 Physiological data

Another approach might be to use physiological evidence of the person's anxiety, stress or shock as supporting evidence for a fall. Bio-electrical signals such as skin conductivity or heart rate can be measured by sensors and the data used to make inferences about the individual's psychological or physical state. Researchers have examined the potential of this type of technique for a wide range of applications, from computer interfaces and consumer electronics (Broek et al., 2010), to reducing road crashes by detecting driver fatigue (Hu et al., 2009).

Looking for physiological responses to a possible fall, such as the elevated heart rate or skin conductivity associated with stress or shock, or even a change in body position, might reduce false alarms and also provide an indication of the severity of the fall. It may also provide information which could be used by clinicians to infer the reason for the fall, for example bradycardia, arrhythmia or hypotension.

Physiological data could also provide information about changes in the person's emotional state, although the difficulties should not be underestimated since they are not expressed as a synchronous and strongly connected set of responses except in the most intense situations or in play acting (Calvo and D'Mello, 2010). Instead, they are usually manifested as a loose association of responses which may be only weakly correlated with each other.

Habitual agitation and anxiety are common in people with dementia (Twelftree and Qazi, 2006; Seignourel et al., 2008; Ballard et al., 1996) and their physiological effects may blunt the sensitivity of a fall detector relying upon them, particularly given the inverse relationship between magnitude and pre-stimulus level in many types of physiological response (Calvo and D'Mello, 2010; Myrtek and Foerster, 1986; Campbell, 1981).

Despite these difficulties physiological measurements have the potential for considerable benefit. Whilst the driver for ongoing kinematic fall detection research is that current techniques are imperfect for fall detection, they may produce much better results when combined with physiological data because the most important consequence of a fall is its effect on the faller.

The faller's experience of the event determines its severity – if the faller is injured, distressed or simply cannot get up then the fall is serious, but if the faller does not suffer any of these consequences then the fall is literally inconsequential, except perhaps as an indicator of falls risk. Two kinetically identical events could produce these two different outcomes, since the outcome is affected by non-kinematic factors such as the intention of the individual and their fragility.

2.4.4.1 The physiological stress and shock of a fall

Nocua et al. (2009) at the Université Joseph Fourier evaluated using solely physiological responses generated by the nervous system for fall detection. The researchers measured skin temperature, skin conductance, and heart rate variability derived from ECG when experimental subjects were pushed over and when they deliberately lay down from a standing position. They were able to detect about 70% of simulated falls (sensitivity 0.70, specificity 0.80) using a support vector machine algorithm. This classification algorithm works by using supervised learning to define the different classes – fall or non-fall – as volumes in a multidimensional space formed from the different sensor inputs. An event is represented by a point in this space and classified according to its proximity to the different volumes. Although the results fell below the requirements of a practical fall detector, it did show the potential value of evidence to confirm a possible fall initially detected using an accelerometer.

Nguyen et al. (2009) added an accelerometer-based fall detector to a wearable three channel ECG logger. Fall detection used the accelerometer alone and not physiological data, but the device would also generate an alarm if the heart rate determined from the ECG went outside 40–150 beats per minute.

Kang et al. (2006) incorporated a fall detector into a wrist-worn physiological monitoring device. The device measured blood pressure, blood oximetry, skin temperature and, if the wearer touched a contact pad with their other hand, ECG. The sensors were activated automatically by the fall detection if the wearer did not indicate consciousness by cancelling an audible alarm. This physiological data was not intended to provide confirmation of a fall, but by presenting the carer with an alarm and access to this data the carer could assess the severity of the situation.

Kinematic sensors can obtain data from almost body location, although usefulness of their data is closely linked to the location. There is a much stronger interplay between the fall detector site and the physiological responses which can be used and they also need placing against the skin. For example ECG is not possible at the wrist, although it is on the upper arm (Plessey Semiconductors, 2012). Pulse rate, blood oxygenation, possibly very limited EMG if there are muscles at the site, mechanical shock, skin conductance and temperature are available at most sites if the sensor is worn against the skin. Conversely, some potentially useful physiological measurements are impractical for a wearable fall detector since the device must be small, low powered, comfortable, easy to put on, tolerant of motion and at least reasonably discrete. This means that facial electromyography, EEG, and probably ECG are not viable since these signals are affected by movement and sensor positioning and the sensors are too elaborate or uncomfortable to routinely wear.

The types of sensors which might be situated on the wrist or ankle and might be useful in fall detection are shown in Table 2.4. A factor to consider is that some sensors such as GSR and temperature will give incorrect readings if the skin is wet.

2.4.4.2 Heart rate

The heart rate is a surprisingly rich source of information, since it is possible to obtain information about exertion, respiration and emotional state. It consists of two components, a high frequency component which tracks respiration, and lower frequency structures between 0.003 Hz and 0.15 Hz which are caused by sympathetic and parasympathetic nerve signal interactions, and the baroreceptor reflex (Kleiger et al., 2005). Heart rate variability is a good indicator of emotional response (Appelhans and Luecken, 2006) and its ease of measuring makes it highly attractive for measuring stress, shock and anxiety.

The normal way of measuring heart rate is by ECG, measurement of the heart's electrical activity (Malik et al., 1996). In a clinical context up to 12 electrodes are distributed around the body on adhesive pads to obtain precise ECG signal waveforms for diagnostic examination but for simply measuring heart rate accurately only two are needed. The best location for these are on the chest, across the heart, since the signal amplitude is the greatest close to its source. The heart rate is measured from the rate at which the large and distinctive electrical spike called the QRS complex, shown in Figure 2-1, is produced. This signal is generated by the near-simultaneous depolarisation of the very numerous ventricular myocardial cells (Mohrman and Heller, 2010, chapter 4).

Kinematic sensors	
Accelerometers	Gyroscopes
Barometric pressure sensor	Location sensor
Environmental sensors	
Sound level sensor	Microphone
Camera	Ultrasonic proximity
Physiological sensors	
Pulse rate, shape, magnitude	Blood oxygen level
Blood pressure	Skin temperature change
Skin conductance change	Electromyographic response

Table 2.4: Possible sensors for a wrist or ankle mounted fall detector

Many consumer fitness monitoring devices measure heart rate in this way using a band worn around the chest. The Vigi'Fall fall detector, which uses a sensor package containing an accelerometer attached to the thorax with an adhesive pad, in conjunction with ambient infrared sensors, received a €2 million award in 2013 to add heart rate monitoring through ECG as an additional input to its sensor fusion system (The Engineer, 2013).

However, it would be difficult to incorporate ECG heart rate measurement into a wrist worn sensor because whilst it is possible to measure ECG for heart rate on the upper arm using three sensors spaced radially around it (Plessey Semiconductors, 2012) it is not possible just using one wrist.

ECG can be measured with voltage sensors attached to both wrists, but unfortunately both wrists need to be connected to a common reference voltage. The wrist worn ECG sensor built by Kang et al. (2006) and described in Section 2.4.4.1 required the wearer to touch an electrical contact on the device with the finger of their other hand. Whilst this is a elegant solution to the problem they were trying to solve it is impractical for automatic fall detection.

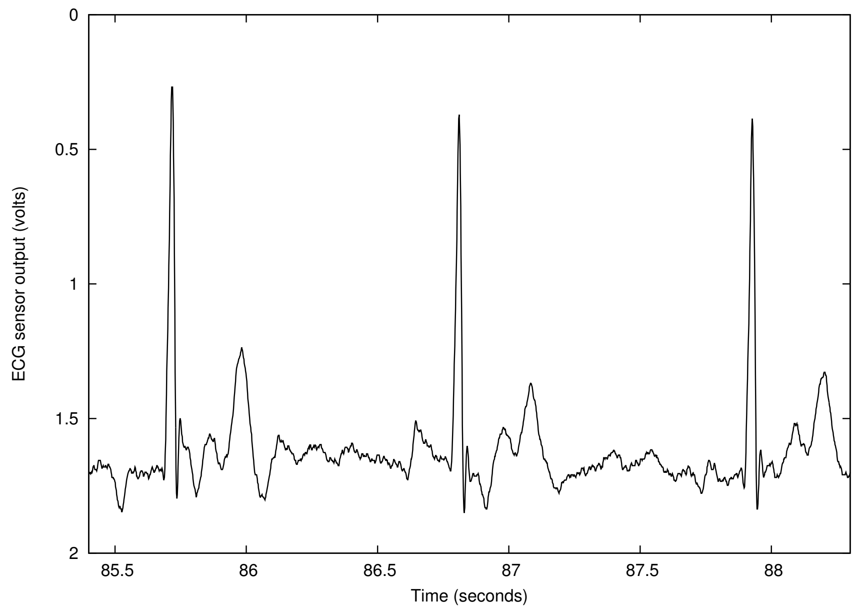


Figure 2-1: Heart rate is determined from an ECG signal by measuring the interval between the large QRS spikes produced by the depolarisation of ventricular muscle at the start of its contraction. Contrast with the gentler, much less sharp photoplethysmographic pulse peaks in Figure 2-2.

2.4.4.3 Pulse rate and photoplethysmography

The heart rate can also be measured through its effect on the vascular system. During systole blood is pushed out of the ventricles to cause a short lived blood pressure rise in the vascular system. The rate of systolic pressure peaks is the pulse rate, and can be measured directly or from its consequences, such as the corresponding variation in arterial blood volume as they dilate and contract under the fluctuating fluid pressure, and blood velocity variation. Photoplethysmography is commonly used, although other techniques are available such as electrical impedance plethysmography (Kristiansen et al., 2005) and Doppler ultrasound measurements.

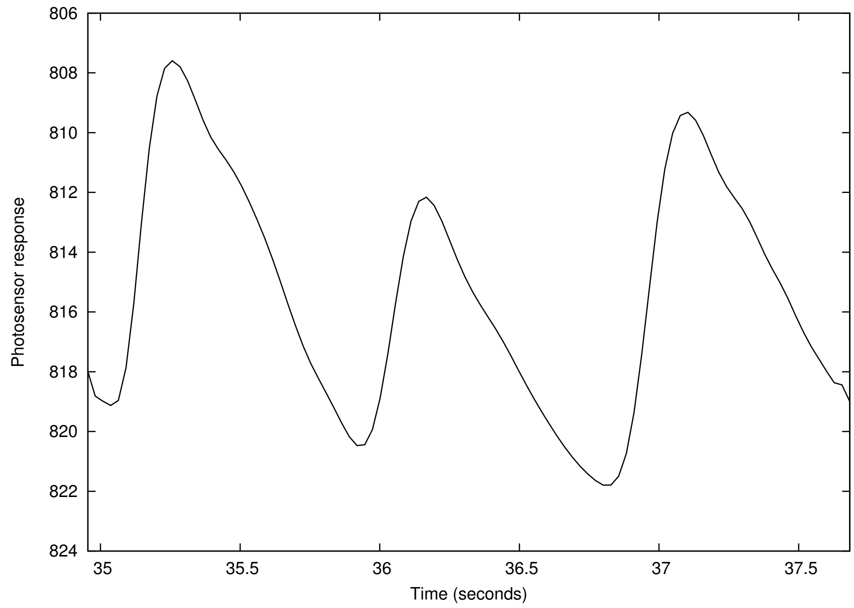


Figure 2-2: Pulse as measured by a reflection photoplethysmography sensor on the upper left forearm. Compare with the ECG trace shown in Figure 2-1. Photoplethysmography waveforms are usually shown inverted, as here, since the maximum blood volume corresponds to maximum light absorption and thus the minimum reflected light intensity at the photosensor. Note from the y axis that the waveform represents only a small variation in the overall light intensity.

Blood velocity is measured using Doppler ultrasonics, and a range gate allows the blood flow at different tissue depths to be measured, and combined with a scan across the surface of the skin allows a three-dimensional model to be constructed (Atkinson, 1982). However, these measurements require excellent acoustic coupling between the sensor and the skin, which would make the technique difficult in a consumer-oriented device since achieving this usually requires gels.

Photoplethysmography is a common technique for pulse rate measurement. It uses changes of 1-2% in light absorption by the microvascular structure in skin tissue caused by the change in volume of blood (Lindberg and Oberg, 1991) and the orientation of the red blood cells produced by the pulse, and can be successfully carried out at many more body locations than ECG measurements. The signal also encodes respiration rate since respiration slightly modulates both the pulse rate and the much larger non-pulsatile optical signal (Allen, 2007).

Transmission mode photoplethysmography has light traversing a thin piece of tissue such as an ear lobe or fingertip, whilst reflection mode places the light source and photosensor side by side so that the light intensity reflected and scattered back by the tissue is measured. Reflection photoplethysmography offers many more choices for placement than transmission photoplethysmography since there are few locations where the tissue is thin enough for transmission plethysmography to be feasible.

Whilst transmission mode is relatively straightforward, reflection mode is much more dependent upon the structure of the tissue used (Mendelson and Pujary, 2003). A high density of blood vessels in a thin layer provides good results – the forehead especially because it also has a layer of bone to help reflect the light (Mendelson and Pujary, 2003). Other good locations are the ear lobe, the fingertip, the toe and, much less conveniently, the oesophagus (Kyriacou, 2006). Regions with a lower density of blood vessels such as the waist are poor (Mendelson and Pujary, 2003). The wrist is a difficult site compared to, say the forehead (Mendelson and Pujary, 2003) but within the last two years several commercial devices have appeared which measure the pulse at the wrist.

Red or near infrared light are often used because they have the best skin penetration, and are essential for transmission photoplethysmography. Shorter wavelengths are strongly attenuated by melanin whilst wavelengths longer than infrared are strongly absorbed by water (Allen, 2007). Blood oxygen level can be measured using an extension of photoplethysmography, called *pulse oximetry*. Two LEDs are used, one emitting light at a peak of 660 nm (red) and the other at 940 nm (near infrared), and the blood oxygen level is calculated empirically from the relative absorption of the two wavelengths by oxyhaemoglobin and deoxyhaemoglobin (Mendelson and Pujary, 2003) since 660 nm light is strongly affected by the oxyhaemoglobin/haemoglobin ratio, and light at the longer wavelength barely affected (Mook et al., 1969).

Whilst high penetration is essential for transmission mode plethysmography, green light is superior to infrared for extracting heart rate in reflection plethysmography. Green light penetrates less deeply into the skin and so there is less noise introduced by scattering (Maeda et al., 2011, 2008), and because the modulation depth for green light is greater, probably because it is more strongly absorbed by blood (Tamura et al., 2014; Cui et al., 1990). This is particularly important in cold temperatures when the reflected pulse signal strength is very reduced by vasoconstriction.

Performance can be improved by increasing either the incident light intensity, or the photosensor sensitivity, usually achieved by more LEDs, larger or more photosensors; and by improved signal processing (Fu et al., 2011). Unfortunately these techniques must be used with care in a battery powered portable device since they all increase power consumption and so reduce battery life.

However, whilst the heart rate is measured from the ECG by looking for the sharp QRS peak, the photoplethysmography signal has a much less steeply rising and falling signal with broader and less well defined peaks which makes precise measurement of pulse rate harder (Gil et al., 2010). The finite left ventricular contraction time, the elastic arterial walls, respiratory movement, and slow (0.15 Hz) cyclic vasomotor contractions can all change the shape of the pulse wave in transit from the heart (Bernardi et al., 1997).

In addition, whilst each heart beat produces a corresponding pulse pressure wave the pulse rate is not identical to the heart rate because there may be small periodic variations caused by factors such as respiration (Constant et al., 1999) which slightly delay or enhance pulse wave propagation velocity. A consequence is that it is harder to extract accurate timing information from a pulse waveform than from an ECG signal.

Whilst simple heart rate measurement is straightforward, very precise timing is required for accurately determining heart rate variability, the inter-beat variation in the heart rate. However Constant et al. (1999), for example, found that the pulse rate variability measurements derived from finger blood pulse photoplethysmography oximeter readings were only an approximation of the heart rate variability. These researchers used children fitted with pacemakers but having otherwise normal heart anatomy, a group chosen for their highly predictable heart rate. However McKinley et al. (2003) found a good correlation using the same type of plethysmography device with a diverse population of 234 adults for determining heart rate variability and Gil et al. (2010) obtained acceptable correlation between spectral heart rate variability and pulse rate variability whilst subjects underwent tilt table tests, suggesting that pulse rate variability is an acceptable alternative to heart rate variability even when the subject is undergoing some limited movement (Gil et al., 2010).

In conclusion, whilst photoplethysmography produces worse results for heart rate than ECG, it is probably feasible to use in a fall detector even for producing heart rate variability estimates.

2.4.4.4 Pulse shape

Examination of the pulse pressure peak shape measured using photoplethysmography at the index finger tip is used as a diagnostic procedure to estimate arterial stiffness. The shape is a combination of a direct pulse of blood from the heart followed by a wave reflected up the aorta from tissue in the lower part of the body (Millasseau et al., 2006). Since the speed of the reflected pulse is dependent upon the elasticity of the aorta, its arrival time is dependent upon arterial stiffness.

The arterial baroreceptor reflex is an autonomous feedback mechanism for short term blood pressure regulation and ensures that the brain and heart always receive sufficient blood supply (Mohrman and Heller, 2010, page 164). Blood pressure is indirectly measured by neural receptors called *baroreceptors* in arteries in the upper body whose rate of firing is dependent upon both absolute arterial wall stretch and its rate of change. These are found in abundance in the aortic arch and the internal carotid artery. The autonomous nervous system responds to these receptors by adjusting heart rate, cardiac stroke volume and blood vessel constriction to maintain constant systemic blood pressure, thus compensating for body posture. Hence, when someone rises from a supine position to standing blood pressure in the upper part of the body, particularly the carotid arteries supplying the brain, will fall as it rises above the level of the heart and the autonomous nervous system will detect this through the arterial baroreceptors. This will trigger the autonomous nervous system to adjust the cardiovascular system to restore pressure measured by the baroreceptors (Mohrman and Heller, 2010). Tilt tables are widely used for examining normal and abnormal baroreflex responses, and the established method for determining whether impaired baroreflex response is the causes of recurrent syncope (Kenny et al., 2000; Parry et al., 2009).

Linder et al. (2006) looked at pressure pulse shape changes with posture using fingertip and earlobe sensors collecting data over three minutes. They looked at pulse rate, pressure pulse duty cycle, and the pulse width measured at half its maximum amplitude from the fingertip sensor, along with the pulse signal amplitude from the ear sensor. The 11 participants, aged 20–43, performed three trials each in which they rose from supine to standing position after the first minute and then returned to supine after the second.

The researchers saw changes between the supine and standing pose, and when the participant was warned to prepare to stand three seconds before being instructed to do so. They observed that the ratio of the pressure peak width to the period between successive pulses, the systolic pressure peak duty cycle, increased when the participant was asked to prepare to stand, three seconds before standing and again when they were standing. The transition to standing was detected in 31 of the 33 trials with one false positive. Standing was accompanied by an increase in heart rate followed by a greatly reduced amplitude pulse signal measured at the earlobe.

Transitions from standing to supine had a less marked effect, and the best results were 19 out of the 33 trials by looking for changes in width of the pressure peak at its half amplitude point, but this also produced 11 false positives.

Xin et al. (2007) found that the pressure pulse waveform amplitude measured at the second toe decreased in supine participants when the leg was raised, and increased as it was raised to the level of the heart and thereafter declined in 45° reclining participants.

Källman et al. (2013) used photoplethysmography to examine blood flow over bony prominences and found it was affected by body position. This study examined pulse shape in different lying poses to help understand if body repositioning might reduce the incidence of pressure sores. Rathgeber et al. (1996) used the technique to look at forearm blood flow in different emergency recovery positions.

Gravity may also have an effect on pulse shape since body posture may change the direction of gravity with respect to the direction of blood flow, particularly in the low pressure venous system. Hence, someone lying on the ground with their arm by their side may have blood return to their heart more easily than when they are standing. In the latter case the blood will have to flow upwards to the shoulder before descending to the heart and in this case gravity may slow the flow. Similarly the reflected wave travelling up the aorta may be slowed when the person is standing because that artery will be vertical.

Pulse transit time (PTT) is the propagation delay of the pressure pulse from the heart to the periphery and is strongly influenced by diastolic blood pressure (Geddes et al., 1981). It can be measured by timing the interval between an ECG QRS spike and the corresponding pressure pulse seen by photoplethysmography at the finger or toe (Katz et al., 2003). It has a diagnostic role in monitoring instantaneous blood pressure changes during sleep in people with upper airway resistance syndrome since blood pressure falls in response to respiratory obstruction, and rises transiently following its clearance (Katz et al., 2003). Foo et al. (2005a) observed PTT changes between sitting and supine poses in children aged 5–12 measured using a toe sensor but not with a fingertip sensor. A later study (Foo et al., 2005b), measured PTT changes following limb movements to assess their confounding affect. They found that in their sample of 23–33 year old supine subjects, PTT increased by a mean of 43 ms in an arm when it was raised vertically, and decreased in a leg by 28 ms when the leg was lowered to an angle of 45 degrees.

If photoplethysmography is to be used to estimate heart rate, then there is extra information which may be usefully obtained from it.

2.4.4.5 Skin conductance

Galvanic skin response (GSR) is widely used in research as a sensitive measure of emotional arousal (see for example Wu and Ren, 2010; Daltrozzo et al., 2010; Jacobs and Hustmyer, 1974). GSR can refer to two quite different electrical measurements, either the skin conductance or the electric potential between two different parts of the body (Montagu and Coles, 1966). These were originally called *exosomatic* and *endosomatic* GSR respectively (McCleary, 1950) but are now described as the *skin conductance* and the *sympathetic skin response*. Skin conductance is usually used since it is easier to measure and better understood, and changes in it are largely due to the availability of ions linked to the secretion of sweat (Darrow and Gullickson, 1970).

Poh et al. (2010) constructed a skin conductance sensor incorporated into a wrist-band using around $150 worth of components. A similar device is now commercially available which uses dry electrodes, and incidentally incorporates an accelerometer, although its battery life is only 24 hours (Affectiva Inc, 2012). However, in a domestic environment skin conductance may not be so useful because measurements are affected by immersion in water or high ambient temperatures causing the person to perspire.

An accelerometer signal which suggests a fall may be accompanied by a change in the skin conductance, as stress can trigger sweating (Baker and Taylor, 1954). The assumption would have to be that an acceleration signal which was associated with a skin conductance change is a stronger indication of a fall than one in which there is no change.

Of course any arousal may be for a variety of reasons, not necessarily connected with the event which produced the accelerometer signal but that event need not necessarily be a fall. The same objection may be levelled at using heart rate variability, but additional information may be available from the pulse.

2.4.4.6 Temperature change

The temperature at the surface of the skin is affected by the blood perfusion in tissue below it since arterial blood arriving at it will be at body core temperature. Consequently, temperature drops when blood flow is reduced and rises when it increases. Several studies have shown skin temperature reductions in the fingers when people are faced with threatening, anxious or otherwise negative emotional or stressful situations (Butschek and Miller, 1980; Boudewyns, 1976).

Rimm-Kaufman and Kagan (1996) observed hand and face temperature changes in response to threatening personal questions and pleasing film clips using a 0.1 °C resolution thermographic camera, although they saw no significant changes when participants were given difficult mental tasks or shown scary film clips.

A temperature drop in the hands was usually accompanied by a corresponding rise in face temperature. The size of the effect was related to the initial conditions – for example warm skin did not heat up further but the cooling responses were greater. For the threatening situation, the face warmed slightly as the hands cooled. The fingertips showed the strongest effect, followed by the fingers and the palms. Skin temperature might be useful in a fall detector, but unambiguous interpretation is extremely difficult and measurements are affected by clothing and ambient temperature.

2.4.4.7 Conclusion

Accelerometers are currently the best kinematic sensors for fall detection, although an excellent indoor localisation system, if it were available, could be better. Gyroscopes may be a useful adjunct, although on their own they do not measure the right kind of movement and so cannot replace accelerometers, and barometric pressure sensors can provide useful information. However, current models of miniature electronic gyroscopes and barometric pressure sensors are handicapped by high degrees of drift and noise.

Physiological sensors are not effective on their own with simulated falls but may be helpful in more realistic situations. Of the limited range of physiological parameters which can be measured at the wrist, the pulse is the most useful since it can provide an estimate of heart rate, respiration rate, emotional arousal from heart rate variability and perhaps body position from the pulse shape, and relative blood pressure through pulse amplitude. In addition, baroreflex responses might be detected which are a direct consequence of body pose changes.

Since physiological measurements are usually carried out in a clinical context, the body position, the subject's anxiety and other factors which may affect the reading are usually confounding factors that upset the measurements and the emphasis is normally on eliminating their effect. However, the situation is reversed in wearable fall detectors where these are the factors of interest, and variation in the baseline clinical readings between individuals is the confounding factor. Also, in a clinical context there is no requirement for an algorithm to extract body pose since if required the clinician can instantly determine it by direct observation.

Of possible environmental sensors, a camera could provide useful information but there are practical problems with ensuring that it has a usable view. The usefulness of a microphone is less certain.

The general conclusion from this short review is that accelerometers are currently the most effective means of detecting falls, but that precise position and velocity data could help substantially. Using physiological data is an interesting approach, although likely to be ineffective for fall detection on its own. However, the next section explores a specific reason why physiological data may be important in fall detection.

2.5 The falls which matter

There are other approaches apart from just using more sensors. If convenient wearable fall detector packages are not going to be capable of reliably detecting all falls except at the cost of many false positives then perhaps a different approach is needed.

The reason for caring about falls in elderly people is because they are the main cause of serious injury. Some other groups, such as toddlers and athletes, are at greater risk of falling than elderly people but their falls rarely result in serious injury (AGS et al., 2001), so falls prevention and detection strategies for them are non-existent.

Hence, rather than try to detect all falls, and fail, it may be better to only try to detect those falls which cause genuine harm. Roughly half of falls in elderly people result in little or no injury, and a study of 191 falls in elderly care homes found a similar proportion are able to stand without help (Bueno-Cavanillas et al., 2000).

It is still useful to detect these cases so that the carer can help the person up and comfort them, but it might be argued that these cases are not *essential* to reliably detect.

It would be desirable to detect a fall which left the person distressed but without serious injury, although perhaps some minor cuts and bruises, and from which they were able to get up. It would also be useful to detect other falls as indicators of physical deterioration and increased risk of injury. However, if there is a choice it seems far better to reliably detect falls which cause serious harm rather than unreliably detecting all falls. The failure to detect even one serious fall can have life shattering consequences. Circumscribing the problem to serious falls may help make the wearable fall detector reliability problem more tractable.

To some extent this has been tried before – an interesting aspect of what was probably the first academic paper on a fall detection alarm system, Williams et al. (1998a), was that it did not raise an alarm for all falls. It only raised an alarm if the person failed to get up within 20 seconds, although it logged all impacts. Bourke et al. (2008b) gathered 183 hours of data from a fall detector incorporated into a custom vest which generated both fall event and fall recovery events. These devices implicitly use the wearer's response to the fall – whether they stood up or not – in the algorithm to determine if the fall was serious or not. The effect being sensed – whether or not the wearer stood up – was dependent on an aggregate of physiological and somatopsychic factors such as injury, shock and pain. A similar philosophy is implicit in those systems which can detect falls through longer term inactivity.

Hence, the falls the detector must be sensitive to, are probably:

- Serious injury. About 5% of falls cause a fracture, of which a fifth are hip fractures, and another 5-6% cause serious non-fracture injury (Masud and Morris, 2001)
- Unconsciousness 0.3%. Rubenstein (2006) examined six studies and found a range of 0–3%.
- Unable to get up within 5 minutes. Asbjørnsen et al. (2000) found 25% of 206 people were unable to get up within 2 minutes. Median age was 82, range 59–97.

To some extent fall dynamics can be surmised from injuries, for example a hip fracture (which affects 15% of the people hospitalised) may be indicative of a sideways fall (Nordell et al., 2000; Hayes et al., 1996) or a fall from standing or walking very slowly (Cummings and Nevitt, 1989). Using kinematic sensors to determine the severity of a possible fall is fraught with difficulty since a gentle fall arrested by a fragile part of the body, such as sideways onto the greater trochanter, can cause serious injury whilst a much more kinematically dramatic fall onto a more resilient part of the body may not.

However, it may be that fall detectors should be optimised to detect those types of fall which are more likely to cause serious injury at the expense of less dangerous falls, perhaps more sensitive to a sideways fall than a fall forwards onto the knees since a sideways fall is more likely to fracture the hip (Parkkari et al., 1999). Tolkiehn et al. (2011) reported an experimental accelerometer/altimeter based fall detector which identified the fall direction to assist in diagnosis of injuries or cause of the fall.

Cerebral concussion is a concern because someone with concussion may be able to rise following a fall and be apparently uninjured. A symptom of concussion is a short period of unconsciousness usually lasting 1–3 minutes, and sometimes followed by a brief convulsion (Ropper and Gorson, 2007). It is caused by the brain being jarred, causing neurons to be stretched or twisted and then elastically rebound (Shaw, 2002). Full recovery can take 6 weeks.

Because concussion is caused by a sudden and large kinetic force applied to the head but not necessarily to any other part of the body it is doubtful that any accelerometer based fall detector not mounted on the head would be able to warn of a risk of mild concussion if the person did not lose consciousness or was only unconscious for few seconds. For example, a gentle settling to the ground accompanied by the head striking a table might cause concussion but no other injury.

A key question about fall detection is what the definition of a fall should be, what events must be detected. This section argued that whilst fall detection research is generally focused on the kinematics of falling, there may be benefits in shifting some of the emphasis towards the varying consequences of different types of fall.

2.6 Revisiting the dynamics of a fall

Having considered the sensors it is necessary to consider how the data from them can be processed. From the perspective of detecting a fall, the event can be divided into different phases, and different sensors can detect a signature for each (Doughty et al., 2000).

Noury et al. (2008) proposed a four phase model, of prefall, freefall and impact (the "critical phase"), postfall and recovery. The recovery phase, where the person either gets up or is helped, is significant since it takes a much broader view of falling. Other versions of this model have more recently been proposed by Abbate et al. (2010) and by the EU FARSEEING project (Becker et al., 2012), notably by considering the impact as a separate phase.

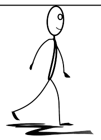
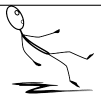
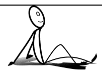
	Phase		Description
	Abbate et al. (2010)	Becker et al. (2012)	
	1. “Activity of daily living”	1. “Pre-fall”	Person performing normal activity
	2. “Hard predictable event”	2. “Falling”	Immediate trigger for fall, for example tripping over something
	3. “Free-fall”		Descent
	4. “Impact”	3. “Impact”	Person hits ground
	5. “Recovery”	4. “Resting”	Person motionless, or nearly so, on the ground
		5. “Recovery”	Person getting back up

Table 2.5: A singe fall event can be subdivided into phases representing different kinematic behaviours. The sub-division allows different parts of the fall to be identified in a sequence to improve fall detector reliability. This table compares the two different five-phase models which have been proposed. (Adapted from Abbate et al., 2010; Becker et al., 2012)

- *Minutes before the fall*

  The person is carrying out an activity of their normal living (Abbate et al., 2010; Becker et al., 2012). Since many falls are caused by a chain of successive failures to avert a fall (Rubenstein, 2006) it is possible that a recent deterioration in gait, balance or cognitive function may have occurred which will contribute to the fall. Some researchers have attempted to produce devices which can warn of an increased likelihood of a fall using ambient systems (Cameron, 1997). During this time the person may stumble but not fall, or may carry out some activity such as sitting which might have some characteristics of a fall (Abbate et al., 2010). The FARSEEING project expert panel recommended that following a possible fall at least one minute’s worth of data prior to the fall should be available (Becker et al., 2012).

- *Seconds before the fall*

There is perhaps an increased likelihood that the person is in a location and time that falls are common. Some event, or chain of events, occur which are the immediate cause of the fall (Abbate et al., 2010).

- *Start of the fall*

  The fall is triggered by a “hard predictable event” (Abbate et al., 2010) such as a trip, stumble, or seizure and is an uncontrolled acceleration under gravity towards the ground, which is usually registered by the accelerometer as near free fall. There may be some rotation of the body, which will produce acceleration signals in the sagittal or coronal planes of the body, or which may be detected by gyroscopes if the detector is appropriately placed. Since the person is descending there may be an increase in air pressure and perhaps changes in environmental electric and magnetic field strength.

  Some experimental pre-impact fall detection systems have been built which look for this acceleration, with the intention of triggering protective mechanisms such as air bags on hip protectors before the person hits the ground (Wu and Xue, 2008).

- *During the fall*

  The free fall continues for 0.4 s to 0.8 s unless it is arrested by striking some object (Becker et al., 2012), during which the individual is startled, causing a wave of activity across many muscles which can be detected by EMG (Bisdorff et al., 1995). Onset of startle is about 20 ms later in people in their seventies than in younger adults (Bisdorff et al., 1999). The person may attempt to arrest the fall by rapid limb movements or seek to protect their head although these do not start until 120 ms to 200 ms into the fall (Becker et al., 2012).

- *Impact*

  The individual experiences a sharp upward deceleration as the floor, or other object, arrests the fall. There may be an audible sound or vibration. If the fall is onto an object, then their body may be twisted. There is a single point of initial contact, followed by other contact points. They may experience forces which overload them causing fractures, haemorrhages or other damage. From the fall detection perspective the impact provides the largest and most distinct accelerometer signal (Becker et al., 2012) which is critical to most fall detection algorithms.

- *Milliseconds after impact*

  There are vertical oscillations in acceleration as the energy of the fall is dissipated by the person and the surface rebounding. Shock waves travel through the body and the surface that they have fallen onto, with reflections at density and stiffness discontinuities. The shock waves may cause audible sound and vibration. They are dissipated by being converted to heat, although they may carry sufficient energy to cause damage to internal body structures.

- *Seconds after impact*

  The person undergoes shock and may lie stationary for seconds, or minutes, whilst they recover from this, although sometimes they will immediately recover.

- *Seconds to minutes after impact*

  They may be calling out in distress and there may be an increase in arousal or shock. If the person is conscious then they attempt to get up, either on their own or assisted by someone else. They may be unsuccessful in standing, and move around the floor without getting up. The fall detector must generate an alert if they are unsuccessful in standing. They are probably distressed, and also possibly injured which would certainly require the fall detector generate an alert. It is this period which may provide the confirmation that a fall has occurred.

  Becker et al. (2012) suggested that the recovery phase should be monitored in detail to improve the medical response. If the person successfully stands up, aided or unaided, then the problem becomes one of finding out if they are injured. If they are unable to stand, and the preceding steps were accompanied by the acceleration, kinematic and physiological signals that this was an unplanned event then a serious fall has certainly occurred.

  A rarely considered issue in fall detection, and particularly relevant for techniques which rely upon inactivity, such as mains power monitoring systems which raise an alert if there are no power usage spikes associated with boiling the kettle, is just how quickly the alarm needs to be raised. Abbate et al. (2010) states that the alarm should be generated quickly because of the correlation between delay and poor outcome. Whilst the effects of long lie are well established (Bloch, 2012; Bloch et al., 2009), there is no literature examining the detailed trade-off between short intervals – seconds or minutes – and outcome. A more important factor may be how long it takes for assistance to arrive once the alarm has been raised since this is likely to be much longer.

Falls are complex events, and can be usefully considered as a set of stages. Each stage represents an opportunity for a fall detector to examine fresh data to either provide additional confirmation of a fall or to reject the event.

2.6.1 Fall detectors as filters

One way of considering fall detection is to view the fall detector as a filter which constantly monitors its environment, and emits a signal when this monitoring indicates that a fall has occurred. The inputs to the filter are signals from the sensors containing information about the wearer and perhaps the environment. The output is conceptually a zero signal which changes either briefly or permanently to a one when a fall has occurred, as shown in Figure 2-3.

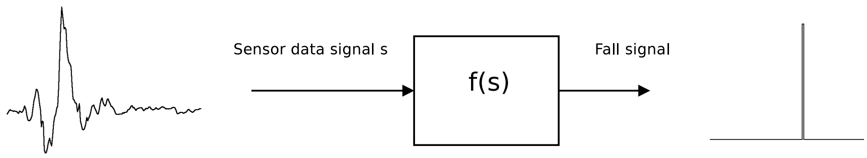


Figure 2-3: A simple fall detector

This type of filtering system is common in other fields from particle physics experiments to automated detection of infection (Lindenstruth and Kisel, 2004; Kaiser et al., 2014). Multi-level triggers can be constructed where the output from one trigger causes a second or third level trigger to examine data, as in the fall detector proposed in Figure 2-4. Phases describe the fall event, whilst the levels describe the detector architecture, so a three-level, five-phase detector would have three levels of filter looking at variously the pre-fall, falling, impact, resting and recovery phases of the fall.

Another technique of looking at a fall is to take the sensor data as a totality and use it as input to a classifier which determines the likelihood of a fall by balancing evidence for and against. There are many types of algorithms which can do this, including probabilistic and least-squares techniques, artificial intelligence methods, and classifiers such as neural networks and fuzzy logic (Sasiadek, 2002). The advantage of this approach is the ability to fuse different pieces of data together to produce a whole better than the sum of the component parts. There are serious difficulties though, particularly power limitations which mean that sensors may only be powered up when needed.

Complex non-deterministic systems are usually programmed through learning, which requires the system to learn the particular individual's characteristics. The customers of consumer devices may be unwilling to spend the time needed to train the device and so the machine learning must happen automatically, but falls are usually so rare that it cannot be part of the normal training process. Verifiability is also a serious problem – how can the effectiveness of a non-deterministic system be demonstrated given the relative rarity of falls in a single individual. And finally, as the wearer's health changes so learnt characteristics probably need to be modified by continuing training.

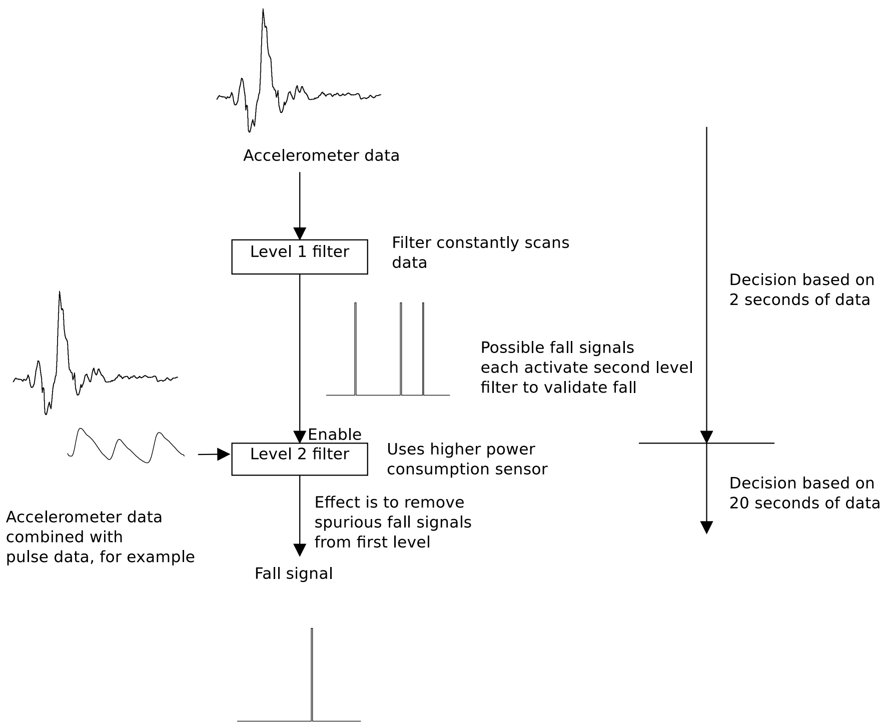


Figure 2-4: Proposed two-level fall detector using accelerometer and pulse data. The use of physiological data to confirm a fall detected by kinematic methods, and the view of the device as a multi-level filter, are novel. The second filter is of greater sophistication than the first one and processes more data, an approach sometimes used outside of fall detection. This differs from a multiphase fall detector (Doughty et al., 2000) where each stage looks for a single kinetic phase of the fall. In the model shown, data from preceeding phases can be combined with new sensor data (including from high power sensors which cannot be left permanently running) and the whole reprocessed to improve confidence that a fall has occurred.

2.7 Summary

Wearable detectors are the most useful type of fall alarm in the short term because of the large existing market, low cost and relative maturity. However, the current generation of devices are unsuitable for people with dementia, and for many others, because of their high rate of false alarms. There are also ergonomic issues with the devices which reduce their take-up.

This chapter reviewed the different sensors which could make wearable fall detectors more reliable at detecting falls.

Whilst many people continue working on refining the accelerometer algorithms, this may not be the only route since there are many other types of sensor available. An important consideration is how easy it is to incorporate these sensors into fall detectors. The small size, simplicity of use and low power requirements of gyroscopes and barometric sensors mean that they are sometimes used alongside accelerometers but the improvement in fall detection efficiency is small. Other types of sensors may be more promising despite the additional difficulties. In particular position and velocity sensors have been shown to be useful, although they are currently difficult and expensive to incorporate into a fall detector.

A different approach is to use the wearer as part of the fall detection system, and look for the physiological response they have to a fall. Whilst this presents practical difficulties and is unlikely to be more than an adjunct to kinematic techniques, there is an important justification for this. It is that the severity of a fall depends solely upon its effect on the faller, and so fall detection must prioritise the detection of falls which cause the most harm. Of the physiological measurements, pulse rate and shape are perhaps the most promising.

This section concludes the main literature reviews in the thesis. The rest of the document is ordered as follows.

- The next three chapters contain an empirical investigation of a specific, novel, technique for obtaining information from photoplethysmography which could be used alongside other data, such as pulse rate and amplitude, which it provides.
- The following two chapters broaden out the technical work with empirical studies to determine the physical form that a fall detector for people with dementia should take.
- The final chapter provides a summary of the thesis and brings the two empirical threads together.

Chapter 3

Body position from pulse shape - a first study

Note that the study described in this chapter was published in Leake et al. (2014)

This chapter describes experimental trials to examine the effect of pose on the photoplethysmographic pulse shape measured at the wrist, in standing, sitting and supine poses, and to determine whether this could be a viable approach to aid accelerometer-based fall detection. The research question was “does the pulse waveform shape provide information about the body position?”

If a fall detector were to use physiological information derived from the pulse rate, then the same sensor may provide other useful information from the photoplethysmography signal. A literature review is given in Sections 2.4.4.3 and 2.4.4.4.

Linder et al. (2006) is the most interesting from the perspective of fall detection, although the original literature search did not identify it, and it was not found until the work described in the early part of Chapter 4 was underway. Linder et al. (2006) looked for immediate photoplethysmographic changes during the transition from supine to standing and back to supine. Supine participants were asked to prepare to stand, and then stand for one minute before returning to a supine pose for a further minute. They found that the transition from supine to standing could be reliably detected from the immediate change in normalised peak width and heart rate measured with a transmission sensor at the fingertip and the pulse amplitude measured using reflection photoplethysmography at the ear lobe, although the changes during movement from standing to supine were less well defined.

The emphasis of the work described in this chapter was not on the baroreflex response during pose transitions, but on the differences between the waveforms once the baroreflex had settled.

3.1 Photoplethysmography

As explained in Section 2.4.4.3, instantaneous changes in the blood volume in tissue can be monitored using reflection photoplethysmography, where the skin is illuminated by visible or infrared light and the returning light intensity measured. The intensity is modulated to a depth of 1-2% by the pulsatile component of the blood flow since blood acts to absorb some of the light. The modulation depth is called the *AC component* (Allen, 2007).

Since greater blood volume within the tissue causes greater light absorption, blood volume maxima caused by ventricular systole pressure peaks produce troughs in light intensity. Plots of the AC component are therefore normally presented inverted, so that their peaks correspond to systolic pressure peaks.

As well as the small AC component, there is a much larger slowly varying DC baseline light intensity, caused by light reflected or scattered from the tissue without being affected by pulsatile blood flow, and called the *quasi-DC component* (Allen, 2007). This is influenced by non-pulsatile blood volume and vasomotor responses, such as those from respiration and vasodilatory thermoregulation (Allen, 2007). The ratio of the two is the *component ratio*, as shown in Figure 3-1. As in the AC component case, increases in light absorption by the tissue *reduces* the DC component amplitude.

The pulse shape at the fingertip is due to the partial superposition of two pressure pulses, as shown in Figure 3-2. The ventricular systole pushes blood into the aorta, and into the arteries branching off it, and this pressure pulse is detected at the fingertip. As the pulse continues along the length of the aorta and into the smaller blood vessels at the end of the thoracic aorta, there are impedance mismatches which produce a reflected pulse. This reflected pulse travels back up the aorta and arrives at the fingertip before the original direct pulse has fully decayed (Millasseau et al., 2002).

The pulse shape measured using optical plethysmography at the index finger, the digital volume pulse (DVP), is used diagnostically. It can reveal cardiac defects such as aortic valve stenosis, and can also be used to estimate the stiffness of large arterial walls as a prodrome for hypertension. This is accomplished through indirect measurement of pulse wave velocity by measuring the time interval between the two pressure pulse peaks. The second peak has travelled an additional distance compared to the first peak, along the full length of the aorta and back again, at a speed influenced by the aortic wall stiffness (Millasseau et al., 2006).

Pulse shape can be measured using several different techniques, for example optical plethysmography, electrical impedance or by instantaneous blood pressure. The measurements could be used as an input to the second level trigger in a fall detector (see Section 2.6.1) to help

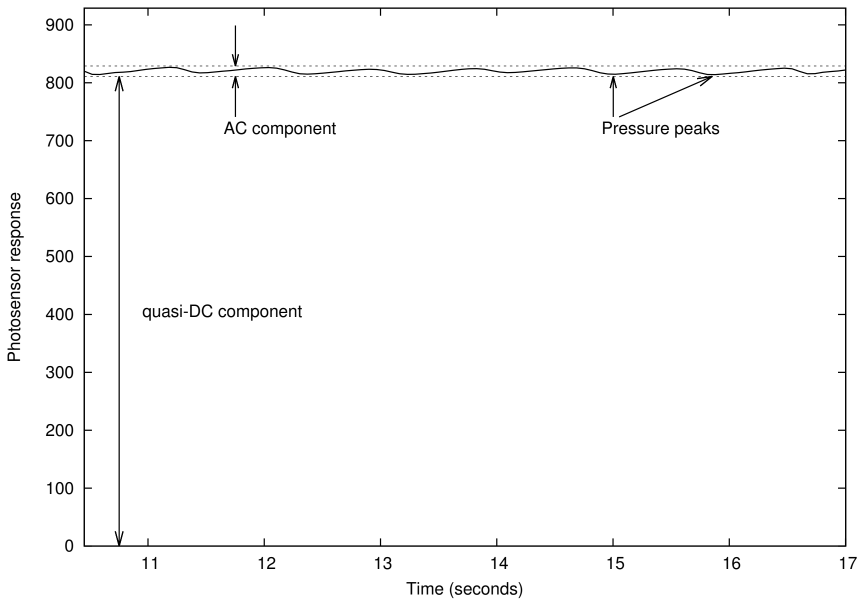


Figure 3-1: Raw reflection mode photoplethysmography data from the upper left forearm (see Section 3.2), showing the quasi-DC component and the much smaller AC component. One unit in the digitised photosensor response signal is about 3 mV. Photoplethysmography plots are usually presented inverted (with the quasi-DC component removed) so that waveform peaks correspond to systolic pressure peaks.

confirm a fall suggested by accelerometer data which resulted in a "fall detected" signal from the first level trigger.

3.2 Preparatory work

Some simple testing was carried out by the author, a 52 year old male, on himself to evaluate whether information about body pose could be extracted from the pulse shape measured at the wrist. The goal was to assess whether a small scale experimental study was justified, by comparing samples of waveforms from each of several body poses to see if there were obvious differences. The experience of capturing and processing pulse waveforms would also generate an understanding of the problems likely to be faced should a larger study be justified.

An inexpensive commercial 3 V reflection plethysmography sensor (Murphy and Gitman, 2012) was used, containing a green LED and an APDS-9008 photodiode-based ambient light sensor filtered by a 340 Hz first order low pass filter, providing the analogue output and implemented as 13 mm diameter printed circuit board. The schematic for the device is shown in Figure 3-3.

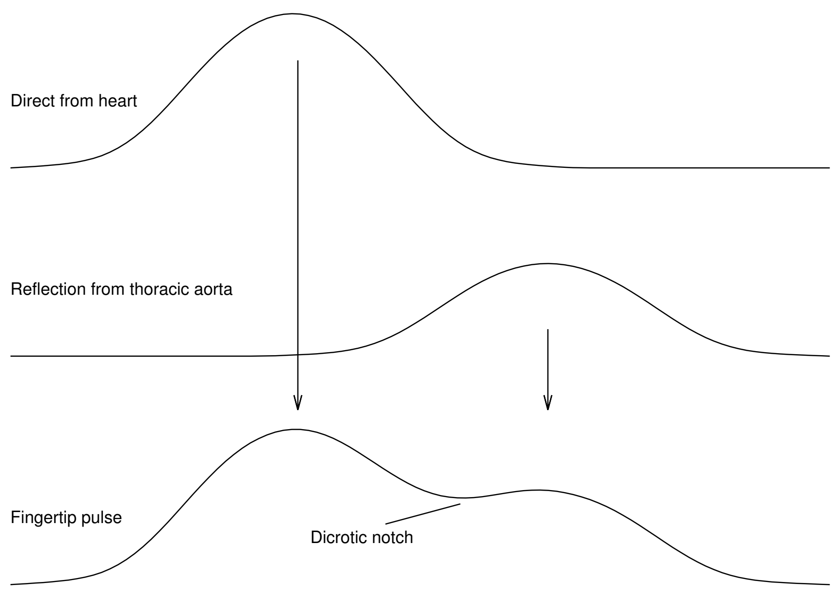


Figure 3-2: Shape of the digital volume pulse measured at the fingertip. Presented in the normal photoplethysmography format with increasing blood volume (= decreasing light intensity) up the vertical axis. The shape is produced by the partial superposition of the direct pulse arriving from the heart and the smaller reflection from arteries at the base of the thoracic aorta arriving shortly afterwards (Millasseau et al., 2002). The minimum between the two pulses is called the dicrotic notch (Allen, 2007).

Although the fall detector was envisaged to be wrist mounted, the photoplethysmography sensor was insufficiently sensitive to resolve the pulse shape at the wrist, and so was taped to the upper left forearm where the pulse signal was much stronger. The left arm was used because of the shorter arterial connection to the heart. In the sitting and standing poses the right arm was placed on the desk, or across the abdomen at waist height respectively. The pulse signal was recorded for approximately 90 seconds in a range of poses which included:

- Sitting at desk, left arm on desk
- Sitting at desk, left arm hanging down
- Sitting at desk, left hand on head. Elbow sideways to body
- Standing, arm hanging by side
- Supine on back with arms by side

The sensor output was digitised by an Arduino Uno R3 microcontroller board (D'Ausilio, 2012) and transmitted via USB to a laptop as shown in Figure 3-4, using a program provided by the sensor manufacturer but modified to increase the sample rate from 50 to 200 samples per second. A Java program was written for the laptop to record the data transmitted by the Arduino. It used a classic multi-threaded producer/consumer architecture, with the producer thread reading data from the serial link and copying it to a thread-safe queue, and the consumer thread removing elements from the queue and writing them to a file. It also provided a realtime graphical display of the data, implemented using JFreeChart, to permit an assessment of data quality before and during data acquisition.

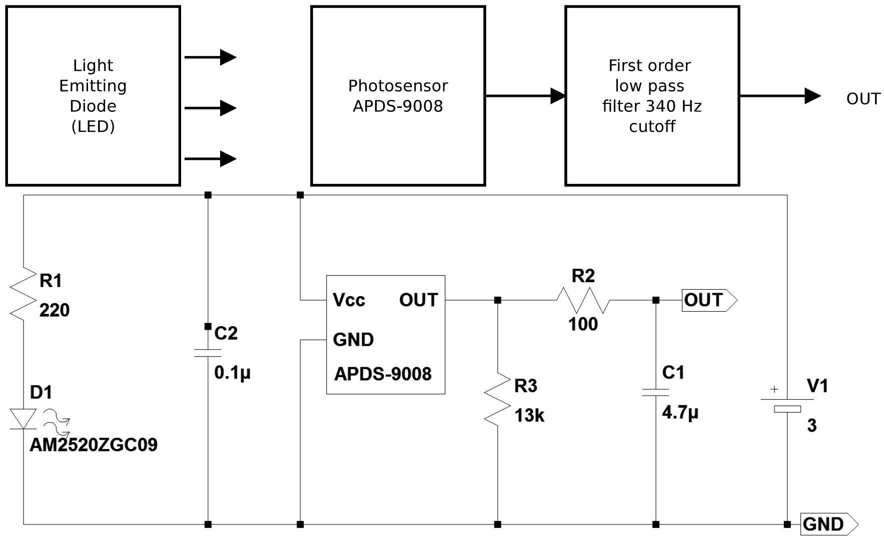


Figure 3-3: 3 V pulse sensor block diagram and schematic. This inexpensive open source commercial device, designed by Murphy and Gitman (2011), and licensed under the TAPR Open Hardware License, uses an APDS-9008 analogue photosensor. There is no filtering to remove the quasi-DC component, so the AC component is only a small part of the output signal amplitude. This means that it is only suitable for sites where there is a relatively large component ratio such as the earlobe and the fingertip. However, an adequate signal was obtained on the upper forearm near the elbow even if was not sensitive enough to capture the pulse at the wrist.

3.2.1 Analysis method

The raw data was very noisy because of its low amplitude and the presence of motion artefacts. A Java program was written to carry out the signal processing steps required to mitigate the noise, split the datastream into individual pulses and characterise their features. A feature or characteristic used by a classification algorithm, for example one which classifies pulse shapes into poses, is called an attribute, and to avoid mixing terminology this term is adopted throughout the thesis. Differences in the pulse curve shape can be readily seen from samples of the raw data in sitting and standing are shown in Figure 3-5 with the quasi-DC component suppressed.

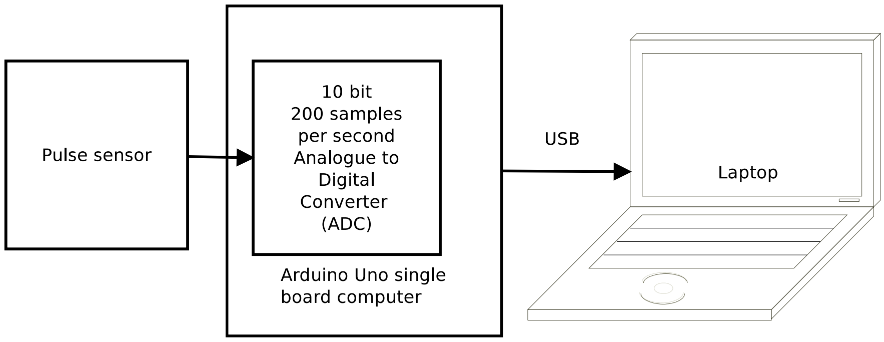


Figure 3-4: Block diagram of the experimental setup used in the preparatory work. The pulse sensor's analogue output was digitised by an Arduino single board computer and transmitted to a laptop over a USB connection for recording.

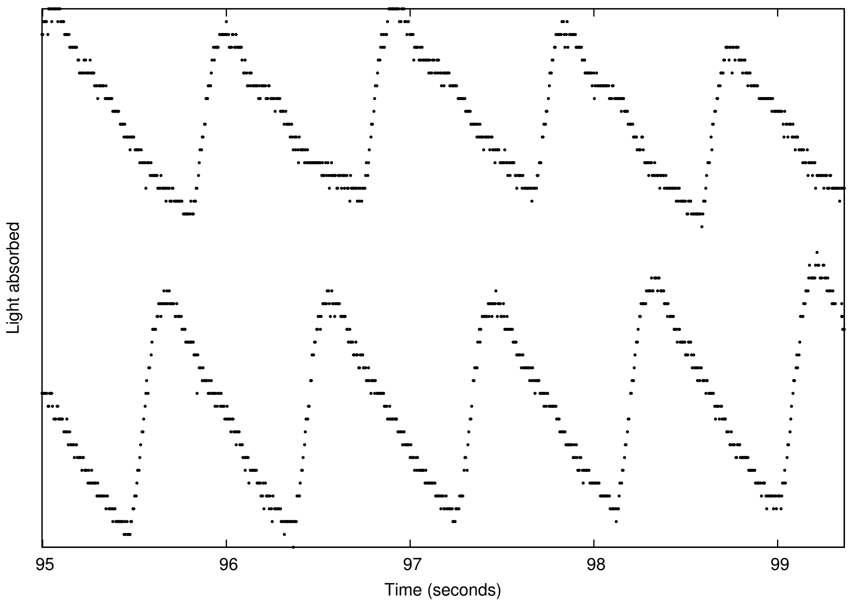


Figure 3-5: Comparison of raw data. The top plot shows the sitting case, with left arm on desk and the lower plot shows the supine case. The signal is inverted so that optical absorption increases with y and the quantisation is due to the analogue to digital converter resolution. A difference in pulse shape can be seen, with the dicrotic notch less distinctive in the lower, supine, pose.

The timestamp was added to each datum by the laptop software and a small amount of jitter was observed in the timestamps. This was probably caused by the data recording process competing for the laptop CPU with other processes running on the laptop which meant that the timestamp was not always calculated at the moment new data arrived.

Once the data was collected, a second Java program carried out further offline processing.

The principal processing steps following data collection, which operated in turn on each file containing the data collected for each pose, are shown in Figure 3-6. The time resolution was reduced to centiseconds during the subsequent processing of the pulse data to mitigate the jitter. The mean of all data arriving in a particular centisecond interval used for the datum value corresponding to that centisecond. With a 200 Hz sample rate this normally meant that two samples were combined, but occasionally a centisecond value aggregated three samples or was generated from one sample.

The sensor measured the light intensity reflected back to it from the tissue rather than the amount absorbed by it, and hence required inversion, which was achieved by the laptop subtracting each datum from 1024. It then applied a 5^{th} order infinite input response Butterworth high pass digital filter with a -3 dB cut-off at 0.2 Hz to remove the quasi-DC component and reduce the variation caused by physical movement artefacts. The code for the digital filter was generated using the online tool at Fisher (2013) and then translated from C to Java. Infinite impulse response digital filters recursively use outputs generated by the filter at previous time steps and therefore require a constant data rate. However, the timestamp jitter meant that a few centisecond values were missing. Where this happened, interpolated data values were inserted into the stream to allow the filters to function.

After filtering, large artefacts were removed by the program examining each one second slice of the data stream and discarding those whose range of values was outside of the 99% percentile of the range of the entire data stream. Prior to this the first two seconds of data was removed since this was greatly distorted by the digital filter settling.

The signal was then split into individual pulses at local minima which were no more than 0.8 seconds apart with a local maximum between them. Any pulse waveforms which had samples deleted by the previous step were discarded.

Once the datastream was split into individual pulse waveforms, further artefacts were removed by discarding pulses which were implausibly long or short for real pulse waveforms or had grossly incorrect shape, for example the amplitudes in the middle of the pulse were greater than near the ends.

The timestamps of individual pulse waveforms were then adjusted so that the peak value was at the same timestamp, effectively aligning them by their peaks, so that an "average" waveform could be produced. Attributes such as the rise and decay times of each pulse waveform were extracted for further analysis.

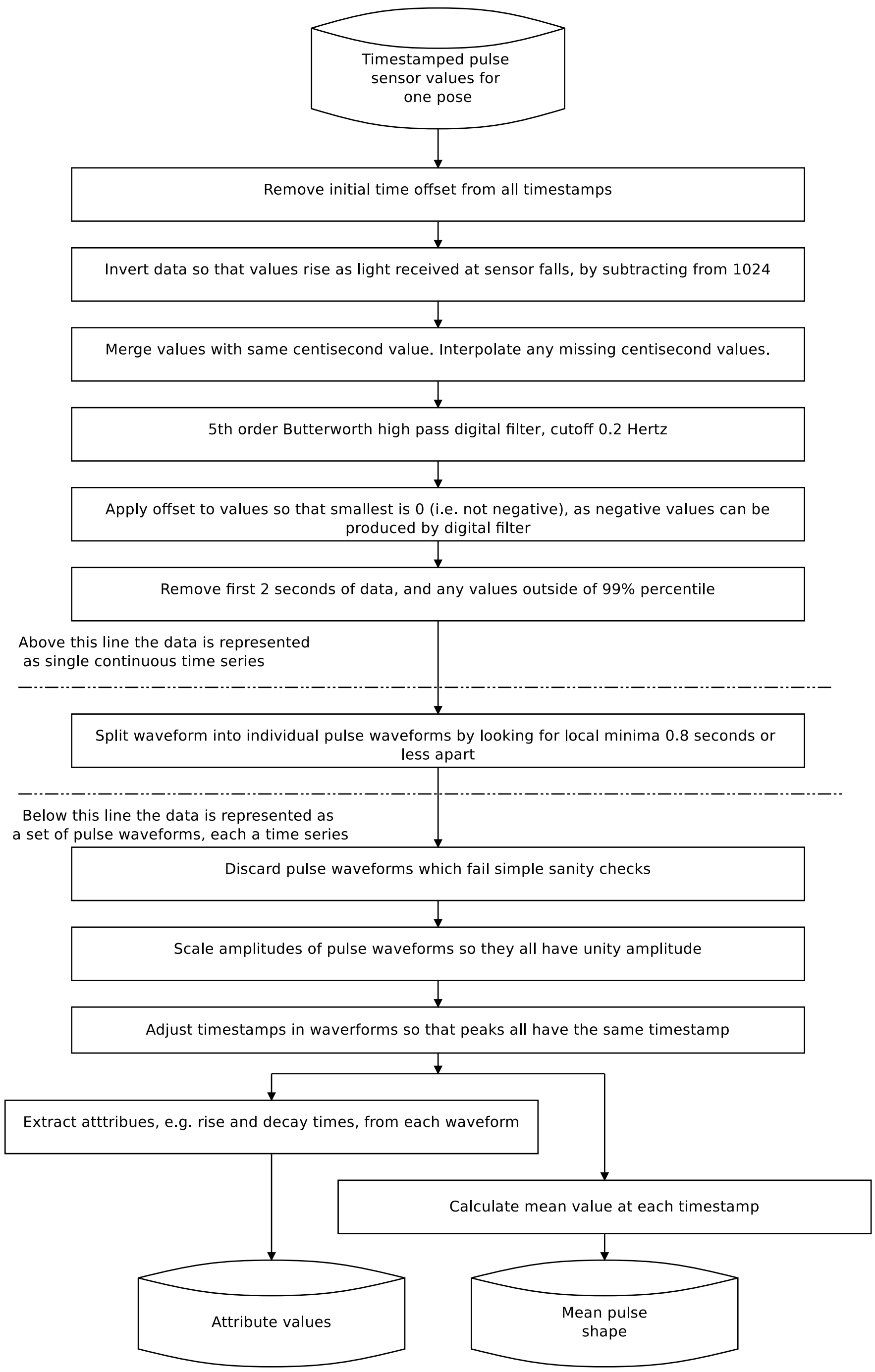


Figure 3-6: Principal processing steps for analysing pulse data collected in the preparatory work, Section 3.2.

3.2.2 Results

The difference between the mean pulse shapes when sitting at the desk with the arms on the desk, and supine on the floor with the arms by the side and parallel to the body is shown in

Figure 3-7.

These curves were produced by scaling the amplitude of each pulse in the two poses to have unity amplitude and then time shifting them so that the pressure peak maxima were all at a fixed zero time offset. The resulting waveforms were computationally overlaid over each other. This allowed a “mean” pulse waveform to be produced for each pose by computing the mean of all normalised pulse curves at each timestamp to provide a visual comparison of the pressure peaks. The mean curves show more noise at each end of the pulse waveform than at the centre. This is because the number of pulses contributing to the mean is reduced at the ends since only very the longest period pulses are providing contributions. Consequently, these plots misrepresent the overall pulse period since the waveform is always the width of the widest pulses. It nevertheless provides a suitable representation of the pulse pressure peak shape.

The tapered shape at the peaks are caused by the quantisation error during digitisation. The maximum in each pulse waveform is normalised to one, but the point immediately before it cannot be less than one quantum, about 7%, below the maximum and the point after it can only be the same as the peak, or more often, at least one quantum less than it.

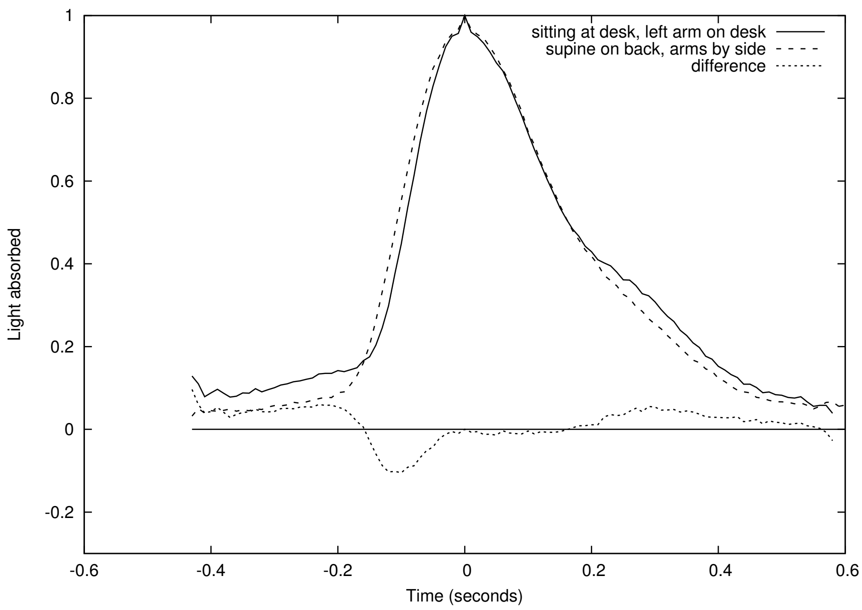


Figure 3-7: Comparison of mean pulse waveform shapes when sitting with left (and right) arm on desk, and lying supine on back with the arms by the side on the floor. In the supine case, the pulse rise time is slightly shorter and the decay is smoother, without the small dicrotic bulge in the second part of the decay seen in the sitting case.

Several simple algorithms were tried to detect the difference. The best was the ratio of the pulse rise time to decay time, i.e. the time for the pulse signal to rise to its peak and to decline from the peak to the end of the pulse. As a dimensionless value this may be less variable between people. The rise time was defined as the time that the pulse took to rise from 10% of its maximum to 90%, and the decay time from 90% to 10%.

The descriptive statistics for this algorithm in the different sitting, standing and supine poses are shown in Table 3.1. Mann-Whitney U tests using R for the likelihood that the supine dataset came from an identical population to each of the other datasets yielded p-values of 10^{-7} or less. The very high probability of independent populations suggested that this has the potential to discriminate between the supine and other poses.

The mean value of the ratio was much lower when supine on the back, 0.39, than in the other poses, with the closest being the sitting poses. This is unsurprising as the hydrostatic pressures in the cardiovascular system are closer to supine when sitting than when standing. However, sitting with the arm on the head produced a mean of 0.48, closer to the supine on the back mean than any of the other sitting poses. An examination of the mean pulse morphologies, Figure 3-8, shows that the despite the closeness of the mean ratios the mean pressure pulse peak shapes were different. In practice the arm on head pose is unlikely in normal activities of daily living and so the proximity of the mean ratio with the supine case was not a concern.

The standard deviations for the ratios showed a large range in values, sufficient to appreciable overlap between the samples, which suggested that using this algorithm alone on single pulses would not provide adequate discrimination in a fall detector.

The range of values seen were slightly greater in arm hanging down poses than with the arm on the desk, and much less with both the hand on the head and the supine pose. Figure 3-9 is a histogram of the values in the sitting with arm on desk and supine poses and the differing spread of values is readily seen.

Figure 3-10 shows the histograms of the two arm by side poses, one sitting and the other standing. There is a wider spread of values than in sitting or supine poses, and the two distributions differ, with slightly differing means and a Mann-Whitney U test shows a p-value of less than 10^{-6} that they both come from the same population.

3.2.3 Discussion

This piece of work met its objective of informing the decision on the viability of a larger study into using pulse shape to determine pose.

There were serious limitations in this work, notably the use of a single individual, the poor resolution of the pulse shapes, the use of the forearm instead of the wrist, and the small number of pulse shape samples collected. Nevertheless, whilst the results of such a limited test were not

Description	Median	Mean	Std dev	Count N	Kurtosis	Skewness
Sitting at desk, arm on desk	0.609	0.604	0.213	72	0.17	0.45
Standing, arm hanging by side	0.843	0.866	0.266	84	2.47	0.65
Sitting at desk, arm hanging down	0.677	0.700	0.242	85	9.22	2.03
Supine on back, arms by side	0.365	0.391	0.104	106	4.32	1.66
Sitting at desk, left hand on head	0.447	0.478	0.127	79	0.77	1.11

Table 3.1: Descriptive statistics for ratio of 10-90% pulse rise time to 10-90% fall time. The algorithms for kurtosis and skewness are those implemented in the Apache Commons Math 3.2 library (The Apache Software Foundation, 2013).

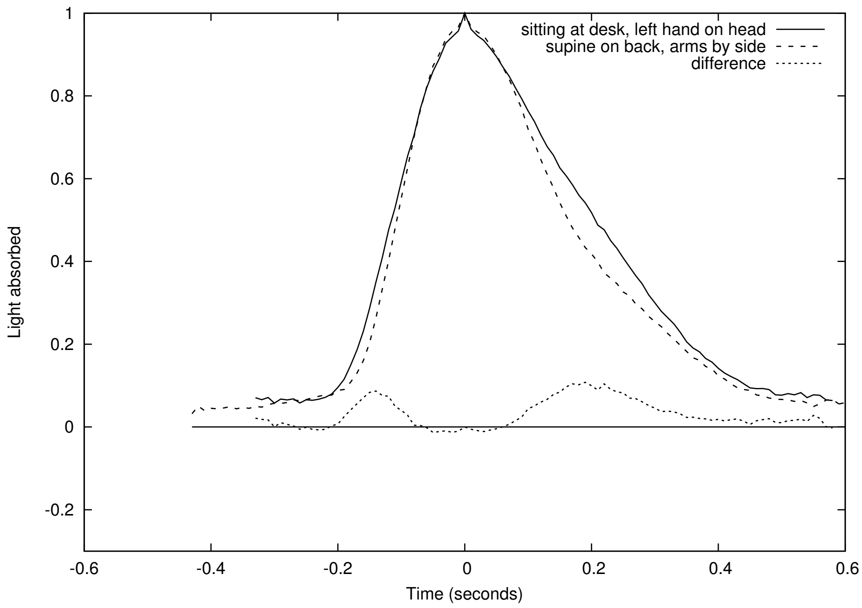


Figure 3-8: Comparison of mean pulse waveform shapes when sitting with arm on head, and supine on back on floor, in the preparatory work. Despite the mean of the ratio of pressure peak rise time to decay time being similar, the pulse shape shows substantial differences.

scientifically conclusive, they amply justified a study involving several people and an improved pulse sensor.

The work also provided a basic understanding of the experimental challenges faced, for example dealing with artefacts and the small signal amplitude. Principal amongst these was the poor resolution of the AC component, shown in Figure 3-5. This was largely due to the retention of the quasi-DC component which was two orders of magnitude greater, as shown

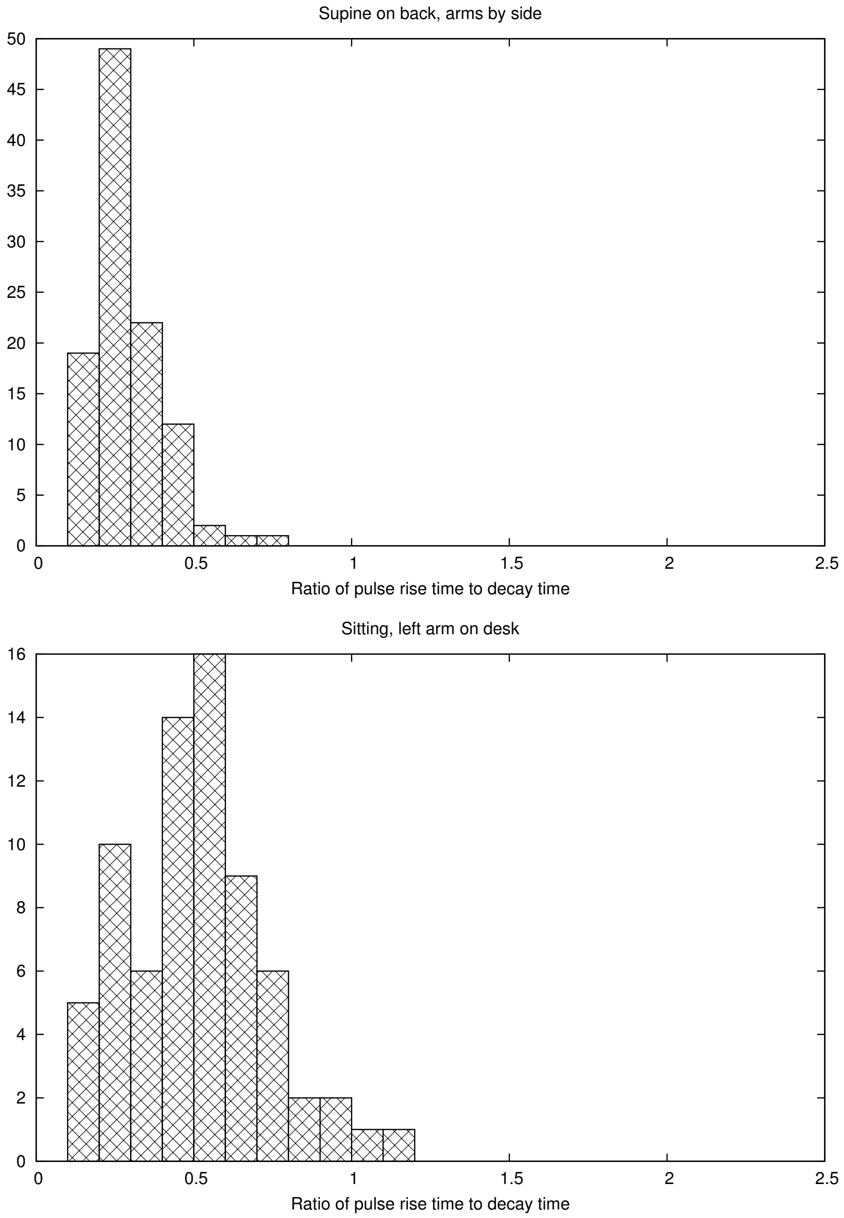


Figure 3-9: Histograms of the pulse pressure peak rise/fall time ratios in the supine pose and sitting at desk with arm on desk, for the preparatory work Section 3.2. Although the two cases show different mean values, there is a considerable amount of overlap of values, which means that using this attribute alone with a few samples to discriminate between the two poses would not be reliable.

in Figure 3-1. The improved pulse sensor must remove the quasi-DC component and amplify the AC component before digitisation to provide sufficient resolution for the pulse shape to be measured at the wrist.

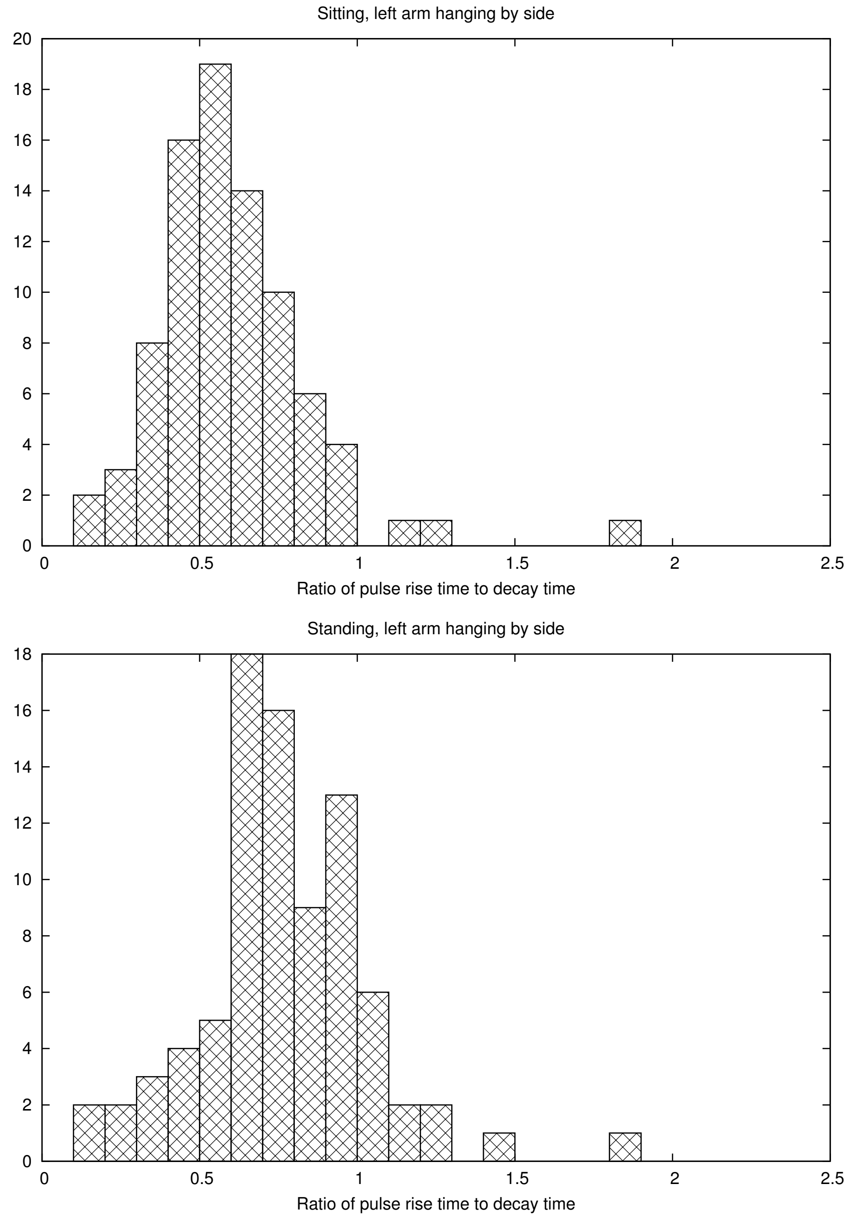


Figure 3-10: Histograms of the rise/fall time ratios for the sitting and standing poses, both with the left arm hanging by the side in the preparatory work, Section 3.2. There are more outliers than in the supine or sitting with arm on desk datasets shown in in Figure 3-9.

3.3 First study

A study was undertaken to test whether the potentially useful effect seen in the preparatory work was present at the wrist. The hypothesis tested was that the pulse shapes measured at the wrist when sitting, lying supine and standing are sufficiently different for automatic discrimination.

3.3.1 Participants

A convenience sample of six participants was recruited from staff and students at the University of Bath and Designability (ages 24–56, median 26.5, 4 female). Written consent was taken and participants received a £10 shopping voucher. Nominally healthy people often have minor medical conditions, and the following exclusion criteria were used:

- Conditions which prevented the participant standing for more than ten minutes.
- Conditions which might grossly distort the pulse shape, for example missing a limb, having a pacemaker, or abnormal heart rate or blood pressure. If the condition was controlled by drugs to bring it back into the normal range then the participant was not excluded.
- Skin conditions which might contaminate the sensor or cause discomfort.
- Insufficient agility to lie on floor and get up again.
- Inability to give informed consent.

Approval was obtained from the University of Bath Health and Psychology departmental ethics committees (see Section D.1). The power calculation was based on the experiment being a repeated measures one, with each pulse waveform being a measurement. Each pose would produce 300–400 usable pulse waveforms and a comparison was to be made between sitting down and each other pose.

3.3.2 Apparatus

3.3.2.1 Pulse sensor

The experimental setup was similar to that of the preparatory work. A pulse sensor was attached to the wrist instead of the upper forearm of the preparatory work, since the fall detector application was envisaged to be a wrist-worn accelerometer-based type. There are no commercial devices designed to measure the pulse shape at the wrist. The "Pulse Sensor Amped" version was used, which is an upgraded version of the inexpensive commercial sensor used in preparatory work (World Famous Electronics LLC., 2015). This has a high pass filter to remove the quasi-DC component, and an operational amplifier circuit to amplify the remaining AC component. The sensor was covered by a clear plastic sticker and sewn onto a fabric band which was closed using Velcro. Whilst the amplifier made the sensor easily sensitive enough to measure the pulse at the wrist further modifications had been made by the designers to distort the pulse signal for easier extraction of the pulse rate which meant that it could no longer be used to measure the pulse pressure peak shape. The output from the sensor when attached to the top of the left wrist is shown in Figure 3-11.

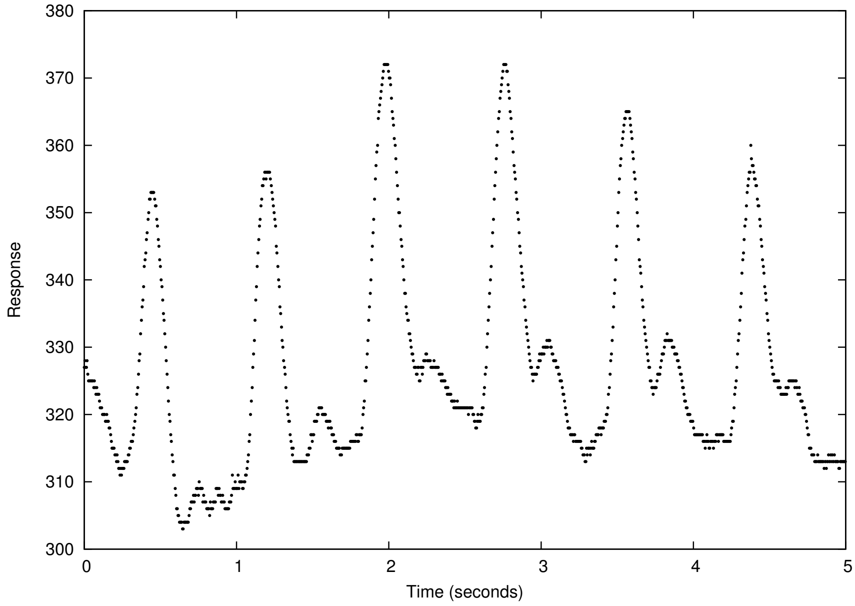
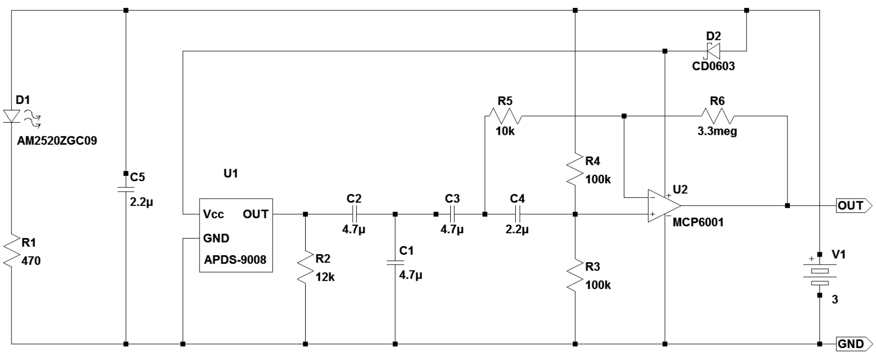


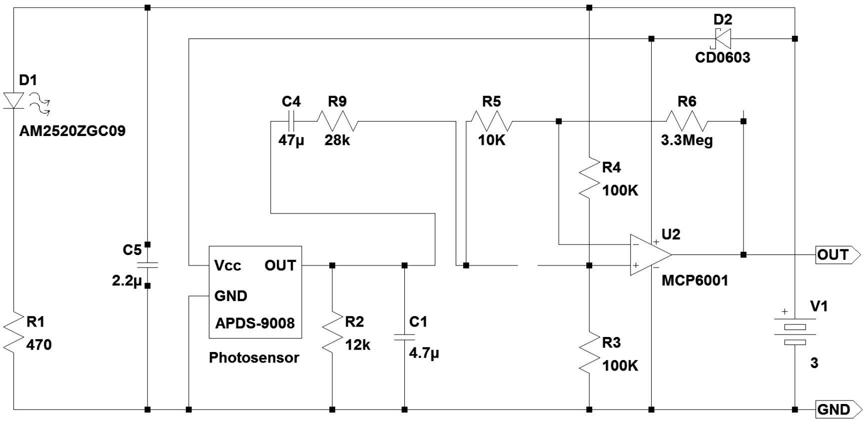
Figure 3-11: The output from the open source commercial Pulse Sensor Amped pulse when located on top of left wrist, 200 samples per second. Whilst the removal of the quasi-DC component by a hardware high pass filter and the amplification of the remaining AC component was a welcome improvement which enabled it to easily sense the pulse at the wrist, the differentiating amplifier circuit distorted the pulse shape. A second small peak to the right of each main peak is caused by the dicrotic notch.

Comparison of Figure 3-3, the original device, with Figure 3-12, the Pulse Sensor Amped, shows the differences. The new circuit operates as an inverting band pass amplifier with a gain of 330 and a narrow peak frequency response at 3 Hz. At the top of the pulse pressure peak, which corresponds to the photosensor sensor output minimum, the sharp change in gradient produces frequency components which include the 3 Hz range which are amplified to produce an output peak from the pulse sensor.

The device could be modified or a new design fabricated from scratch. A new design would allow a clean sheet and produce more desirable features in the device, whilst the surface mount device allowed less scope for modification. However, this was seen as the higher risk choice, since at this stage the author had little experience in electronic design and construction, none in the pitfalls of pulse sensor design, and limited miniature electronics fabrication facilities. Hence, the decision was taken to modify the pulse sensor to produce a device which



(a) Original circuit schematic (design by Joel Murphy, World Famous Electronics LLC. (2015)). The circuit functions as a narrow band pass filter with a peak at 3 Hz and a gain of 330, i.e. signals around 3 Hz are preferentially amplified.



(b) Modified circuit to set high pass cut-off to 0.1 Hz and eliminate low pass filtering. (adapted from Leake et al., 2014)

Figure 3-12: The original Pulse Sensor Amped circuit schematic and the modified version used for measuring pulse shape at the wrist. Both licensed under the TAPR Open Hardware License.

had an amplified pulse shape since the limitations imposed by the design of the existing device were relatively easy to overcome. The circuit was modelled using the LTSpice IV simulator, Figure 3-13a, with the raw photodetector response simulated using data from the preparatory work.

The device was modified to remove the band pass filter and replace it with a 0.15 Hz first order high pass filter to attenuate the quasi-DC component, as also shown in Figure 3-12. The changes were implemented using a through-hole circuit board attached to the wrist strap. The R9 resistor was configurable using jumpers to provide some gain control, at the cost of affecting the high pass filter cut-off. Since a 4^{th} order 0.2 Hz high pass filter would be applied to the data the main effect of modifying R9 would be on frequencies above 0.2 Hz because of the gentle roll-off of the first order analogue filter. Although only a small effect, it was recognised that fixing R9 was desirable.

27.8 kΩ was used in all data taking in the study with the exception of participant 4 supine poses. Unfortunately these had an extremely large pulse signal amplitude which risked saturating the amplifier and R9 was changed to 47 kΩ, which changed the low cut-off frequency from 0.15 Hz to 0.07 Hz.

For convenience through-hole components were used for new components and mounted on a printed circuit board attached to the sensor strap. To conform to the licensing conditions of the original open source hardware Amped sensor, the modifications are also licensed under the TAPR Open Hardware License (Tucson Amateur Packet Radio Corp, 2007).

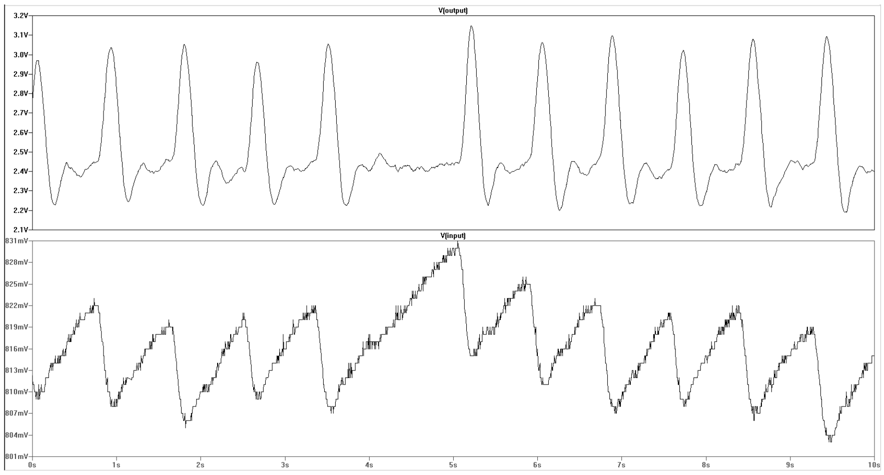
3.3.2.2 Arduino

The same Arduino Uno R3 model was used as in the preparatory work, but to help reduce noise the pulse sensor was powered by two 1.5 V AA batteries in series, also used by the Arduino as the ADC reference voltage. The sensor and Arduino are shown in Figure 3-14.

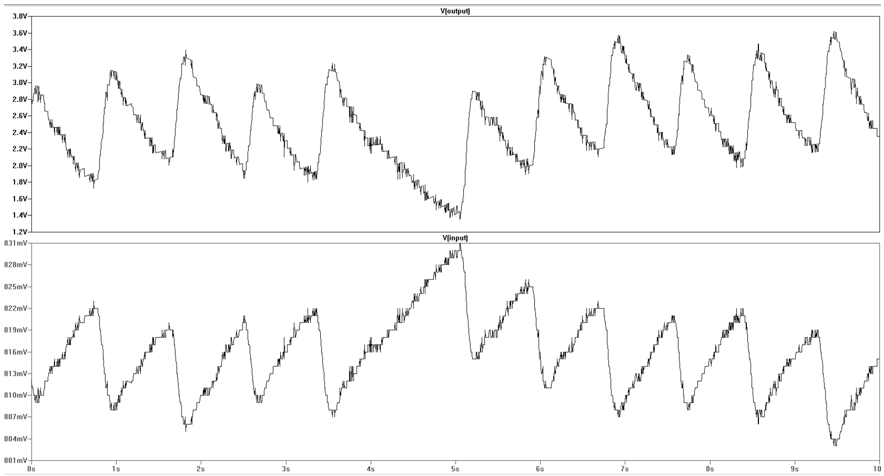
3.3.2.3 Arduino software

The Arduino software was much simpler than that used in the preparatory work, as it did not contain many features of the manufacturer's program which were not needed, such as heart rate calculation. A single thread operating in a loop waited for a synchronisation timer interrupt before reading the analogue input voltage from the pulse sensor. It then formatted the reading into a text message, which included a timestamp, and transmitted it to the laptop. It inverted the state of the LED on Arduino Pin 13 every 100 points sent (i.e. every 0.2 seconds) so that it flashed to indicate that the program was running. The source code is reproduced in Section A.1.

Generating the timestamp in the Arduino eliminated the jitter of the caused by the laptop's soft real time Linux generating the timestamp. The 115200 baud rate was easily capable of supporting the 500 samples per second data rate. This gave a good time resolution with a Nyquist frequency of 250 Hz, comfortably above the 50 Hz mains and 100 Hz fluorescent lighting flicker interference sources. The timestamps were transmitted with a resolution of 1 ms, so that the 50 samples per second data stream would contain a series of odd, or even timestamps. Nevertheless, there was still some jitter with timestamps, probably caused by quantisation errors in the hardware timers. The TIMER0 counter used to run the Arduino `millis()` function, which generated the timestamps, uses the 16 MHz internal clock divided down by 64, so the counter increments every 4 µs, from which it is not possible to accurately time one millisecond.



(a) Simulation of the original circuit, showing how the response is optimised for pulse rate measurements.



(b) Simulation of the modified circuit, showing that it removes the quasi-DC component from the input, inverts and amplifies the AC component.

Figure 3-13: LTSpice simulation of the original and modified Amped pulse sensor circuit. In each case the upper trace is the output from the pulse sensor circuit and the lower trace is input, the simulated signal from the APDS-9008 photosensor, using a pulse signal recorded in the preparatory work. It appears inverted because a pulse pressure peak maximises light absorption and so produces a minimum in the APDS-9008 photosensor signal. (after Leake et al., 2014)

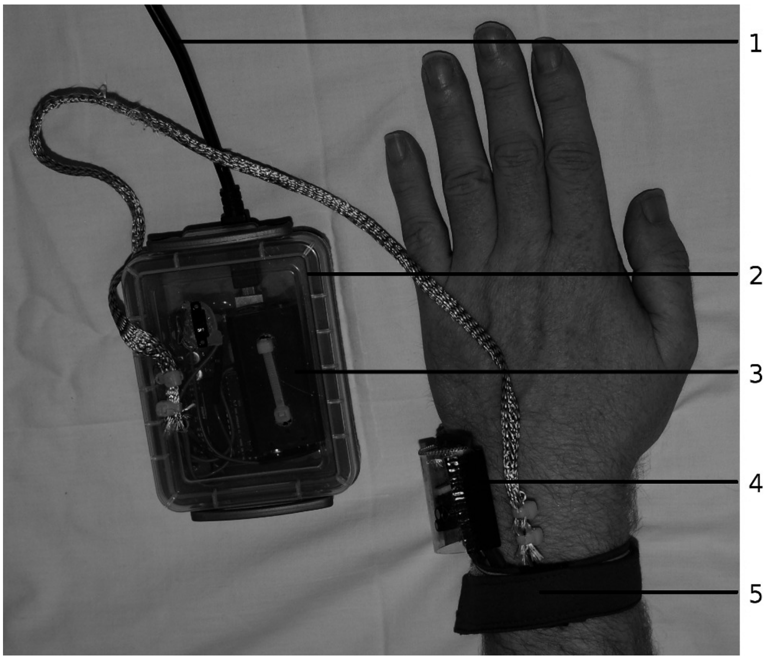


Figure 3-14: The pulse shape sensor hardware

1. USB cable to laptop
2. Arduino Uno R3 (in box)
3. Modified Pulse Sensor Amped underneath strap
4. Additional filtering electronics
5. Batteries powering analogue electronics

3.3.2.4 Laptop data recording

The Arduino was connected to a laptop running an improved version of the original Java data recording program. The program display is shown in Figure 3-15. As with the earlier version it used a classic producer/consumer architecture with one thread, the producer, reading the Arduino data and copying it to a thread-safe queue, and a consumer thread which removed elements from the queue and wrote them to a file.

The user interface was made as foolproof as possible since there are potentially many distractions and problems during a participant run. It prompted for the participant ID, the pose and other pertinent information when the test was set up, and wrote these as comments to the data file. The file would be created in a data sub-directory with the format nnnnnnn.txt, starting with 00001.txt. Each time a new test was started a higher numbered data file was produced, and the time elapsed shown on the display, recording ceased automatically after five minutes. A synthesised example of the output file is shown in Listing 3.1, with the automatically inserted comments identifying the test followed by the timestamp/datum pairs.

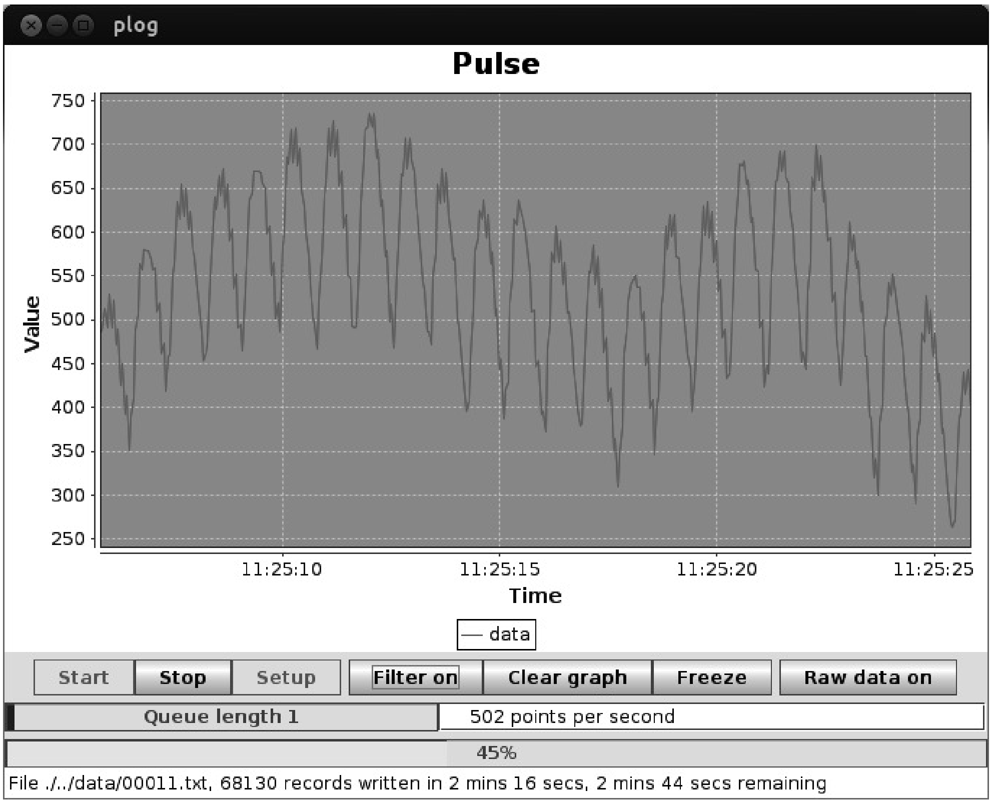


Figure 3-15: The data recording program display.

The display was implemented using Java Swing, and a plot of the pulse waveform was shown using JFreeChart, and showed a sampled subset of the data to keep the laptop processing load reasonable. Problems were seen with early versions of the program where noise on the pulse signal produced a misleading display since only a small sample of points were written. This was corrected by adding a low pass filter on the data displayed (but not written to the file). The data quality was variable because of small signal amplitudes and noise. Experiments were made with automatically assessing the data quality from the pulse data in real time – based on the pulse amplitude – but these were not successful and visual examination remained the main method.

Listing 3.1: Example start of data file showing millisecond timestamped pulse signal readings

```
# VERSION: Plog 2.0
# PARTICIPANT: P5
# LOCATION: Left wrist
# POSE: Sitting at desk, left arm on desk
# SENSOR: 4
# DATETIME: Mon, 24 Jun 2013 14:28:14 +0100
119261 604
119263 583
119265 614
119267 624
119269 642
```

3.3.2.5 Evaluation of the system

The sensor resolved the pulse at the top of the wrist without difficulty, but the signal from the underside of the wrist was smaller and more affected by noise.

The sensor was also noticeably affected by external light, with flicker from fluorescent tubes easily apparent as a high frequency oscillation on the raw data. Black tight-weave cloth was wrapped around the wrist on top of the strap and held in place with a second Velcro strap to mitigate this.

The improved data recording program was easier to use, allowed the data collection to be monitored more easily in real time, and data collection problems to be identified and rectified.

The batteries provided sufficient voltage for the device for many hours. The system suffered from electromagnetic noise, notably mains interference and spikes. Screening of the cable between the sensor and the Arduino was added but this had little effect. Most noise was therefore eliminated in offline processing.

The pulse signal makes up only a few percent of the reflected light, whilst even small movements had a much greater effect, so the amplifier was prone to saturating with even the smallest movement. Depending on the size of the movement the analogue filter took between a few seconds and nearly a minute to settle down again, and there was a similar delay at the start. There was also a lengthy delay of tens of seconds when the sensor was powered up whilst the analogue filter settled.

3.3.3 Method

Each participant adopted a series of poses and five minutes worth of pulse data collected for each pose. Five minutes was selected to provide about 400 pulses, of which 100 were expected to be too distorted by movement artefacts. The usable pulses left would form a representative sample for the participant in the particular pose that they were generated in.

Participants wore the sensor on the top of the left wrist about 3 cm from the wrist joint and data was recorded from the sensor in ten poses. Participants were asked to move and speak as little as possible but permitted to read during the sitting and standing poses. The poses are shown in Table 3.2.

Number	Pose
0	Sitting at a desk with the left arm resting on the desk. Feet flat on floor. Right arm on desk.
1	Sitting at desk as above but with left arm hanging down.
2	Sitting at desk as above but with left arm on head. The elbow was supported by a box for the participant's comfort.
3	Standing with left arm hanging by side.
4	Standing with left arm across right side of chest at level of heart, hand gripping clothing to avoid discomfort.
5	Supine on back with legs straight and arms by side.
6	Supine on back as above with left arm on floor but oriented to be stretched out at an angle of 135 degrees to body (i.e. hand roughly in line with head).
7	Supine on back as above with left arm over right side of chest
8	Supine on left side with the left forearm pointing out from body
9	Supine on right side with left hand on floor

Table 3.2: Poses in first study

3.3.3.1 Offline processing

The offline processing software was based on the code written for the preparatory work. As before, processing of the timestamped pulse data was carried out in two stages. The first represented the data from each participant pose as a time series of values and applied operations such as digital filters to these. At the end of the first stage the time series was split into segments representing the individual pulses and the second stage operated on these. The graphics were produced using the JavaPlot library, which in turn used Gnuplot; and statistical routines provided by the Apache Commons math3.stat package.

In the first stage each individual operation was carried out by a software object which took the time series as its input and produced a modified copy of the time series as its output.

This allowed the sequence of operations to be changed and re-ordered with the minimum of difficulty although at the expense of computational inefficiency in copying large amounts of data.

This scheme allowed the processing chain to be assembled as a list of software objects, each of which carried out one operation on the data (such as low pass filtering). The program iterated through the list, calling each object's `process()` in turn and thus carrying out the processing sequence in the correct order. The output from each object's `process()` method would be used as the input to the next one.

This allowed extremely easy control of the processing steps and since the format of the output from each function object call was the same as its input allowed them to be run in any order, and is shown in slightly simplified form below.

Listing 3.2: Building the data array processing chain

```
private List<TimestampedValue>
    processTimestampedValues(List<TimestampedValue> inputData) {
    List<DataArrayStage> processingChain = new ArrayList<>();
    // Plot some graphs showing samples of the data
    processingChain.add(new Sampler());
    // Subtract initial time offset from timestamps
    processingChain.add(new TimestampBaseliner());
    // Correct jitter in timestamps
    processingChain.add(new TimestampCorrecter());
    // Mark data which hits the buffers
    processingChain.add(new BoundaryMarker());
    // Remove low frequency oscillation caused by movement etc
    processingChain.add(new HighPassFilter(0.2));
    // Remove spikes and mains hum
    processingChain.add(new LowPassFilter(5));
    // Remove two seconds settling time for filters
    processingChain.add(new Masker(0,
              2 * Constants.ONE_SECOND_IN_MILLISECONDS));
    processingChain.add(new Shifter());

    List<TimestampedValue> outputData = inputData;
    for (DataArrayStage stage : processingChain) {
        outputData = stage.process(outputData);
    }
    return outputData;
}
```

Name	type	Description
masked	boolean	Whether the value is to be ignored
value	double	the value.
milliseconds	int	timestamp, measured from the boot time of the Arduino

Table 3.3: Basic representation of timestamped pulse sensor data

In the first stage the data was represented as a list of timestamped data elements, implemented as a Java `ArrayList` for fast access, with the format as shown in Table 3.3. This was implemented as a `TimestampedValue` class inheriting from a `Value` class, since the value/masked combination was used in other places in the program. The modules implementing the different timestamped data stream processing algorithms were implemented as function objects, inheriting from an interface with the following signature. The boolean `masked` was used to indicate that the value was invalid and thus the pulse waveform containing it was to be discarded. This would happen, for example, if the data was clipped at the upper or lower limit of the range of analogue to digital converter output values. Since the digital filters needed regularly spaced readings these values could not be immediately deleted, only flagged for later deletion.

Listing 3.3: DataArrayStage abstract class

```
protected DataArrayStage(Stage stage);
abstract protected List<TimestampedValue>
    run(List<TimestampedValue> inputData);
public List<TimestampedValue>
    process(List<TimestampedValue> inputData);
```

The `process()` method handled logging the operation, generation of output graphs and other intermediate output but carried out the actual data processing using the `run()` method whose implementation was delegated to the subclass which carried out each specific filtering operation. The processing stages were implemented using a class hierarchy where sensible, for example the digital frequency filter classes all ultimately used generic classes which implementing the algorithms described in Allred (2010). Several classes, particularly for different types of filters, were discarded over time as the understanding of the data and the processing steps needed developed.

The significant steps are shown in Figure 3-16, and are as follows.

- Stage 1

    1. Adjust timestamps of all data elements to remove initial offset.

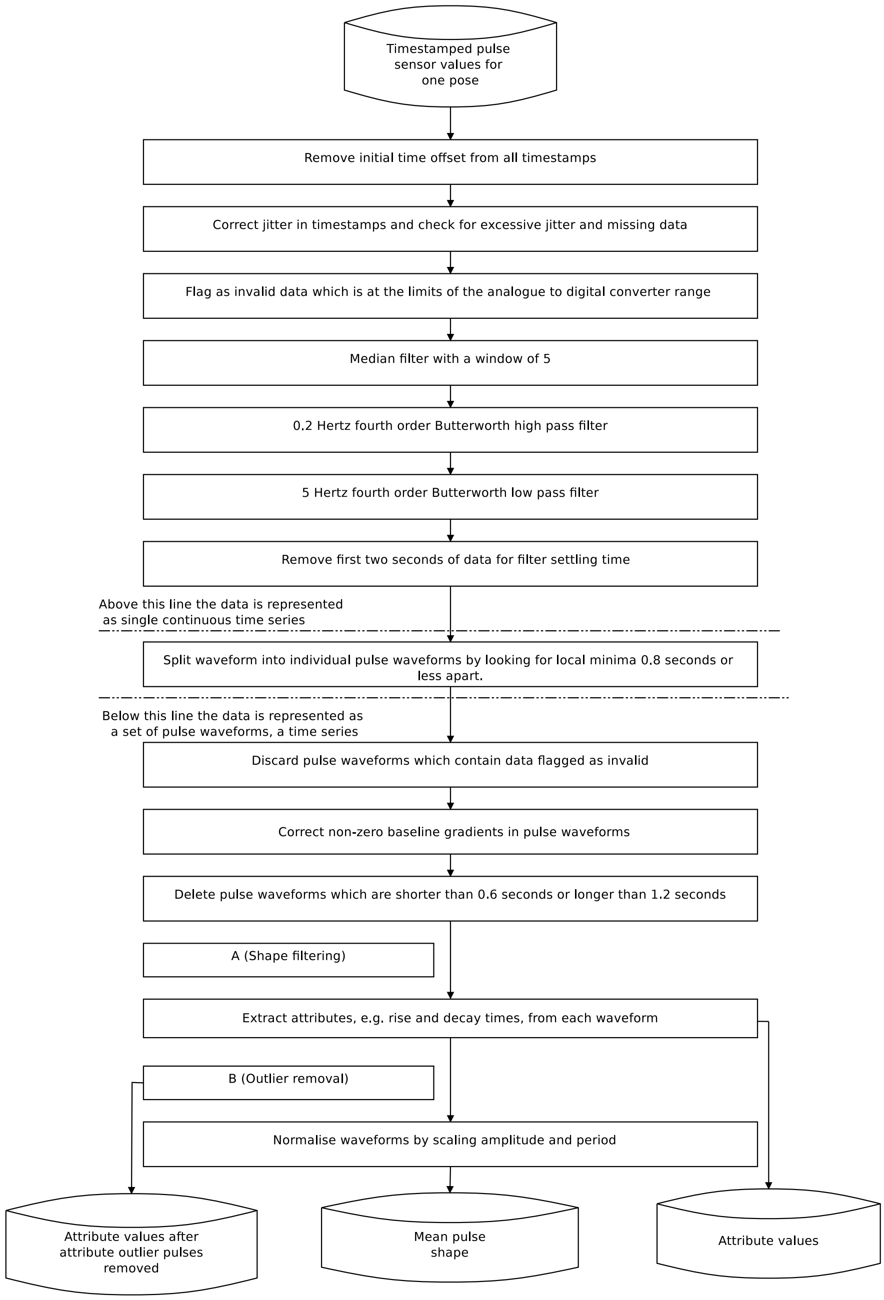


Figure 3-16: Principal processing steps for analysing pulse data collected in the first study. A and B are points where additional modules were inserted into the processing chain. These were a pulse waveform shape filter and a module which removed statistical outliers and the waveforms containing them. These are discussed in Section 3.3.3.2.

2. Adjust timestamps for jitter, checking for excessive jitter and missing data.

3. Attenuate short-lived noise spikes using a median filter with a window size of 5.

4. Remove the remaining low frequency signals using a 4^{th} order Butterworth 0.2 Hz high pass infinite impulse response (IIR) digital filter. Since most of the quasi-DC component was removed by the hardware filter and the signal inverted by the amplifier circuit, these represented the inverted higher frequency portions of the quasi-DC component.

5. Eliminate remaining high frequency noise using a 4^{th} order Butterworth 5 Hz low pass IIR digital filter.

The data stream was split into individual pulse curves by looking for local minima. Each data point was checked to see if it was the smallest in a range of ± 300 ms – half of minimum expected heartbeat period. If multiple minima were found then the mean location was used. This is shown in Figure 3-17.

- Stage 2

1. Pulse waveforms containing data detected during the first two seconds of each run were deleted, to cover the time that it took for the digital filters to stabilise, along with waveforms which were clipped at analogue to digital converter range by excessive amplitude.

2. The average gradient of each pulse waveform was computed from the first and last point. Ones with a magnitude greater than 100 units per second were discarded, otherwise it was assumed that the pulse waveform's baseline changed linearly and it was adjusted assuming a constant gradient to compensate for this slope. This introduced some error as tilting the pulse in this way sometimes had the effect of moving a minimum point.

3. Pulses shorter than 0.6 seconds or longer than 1.2 seconds were deleted as likely artefacts. This step and the previous two eliminated about 20% of pulse waveforms. The distribution of remaining pulses is shown in Table 3.4.

4. The features of interest, or attributes, were extracted from the remaining pulses and tabulated. The attributes are described in Section 3.3.5.

5. Each pulse waveform trace was scaled to a common height and width so that the average could be calculated by conceptually overlaying the pulse curves.

6. The average pulse waveform was calculated from the mean or median of each normalised timestamp value.

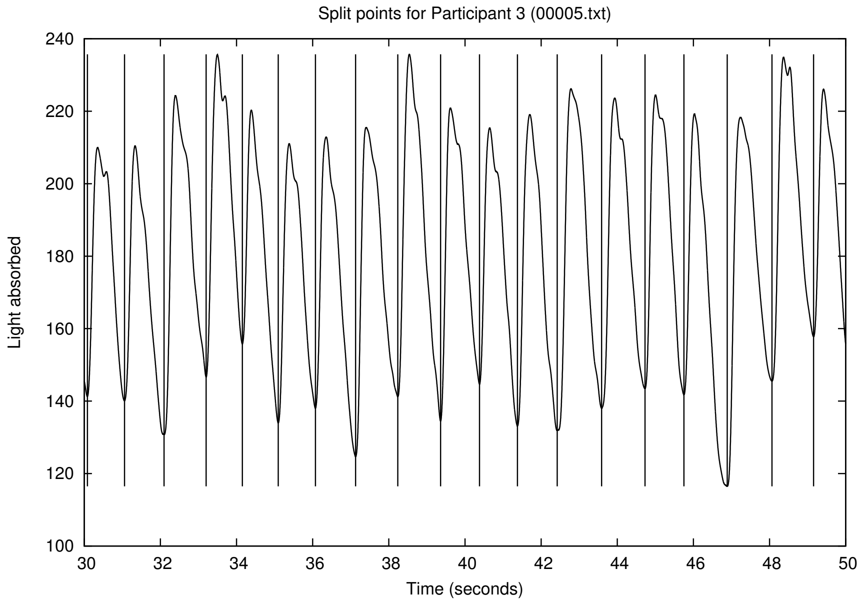


Figure 3-17: Splitting the time series data into individual pulses at the end of Stage 1. This figure shows a portion of a pulse sensor data time series containing 19 pulse waveforms. The data is split into individual pulse waveforms by looking for minimum values separated by at least 0.6 seconds. These are represented by the vertical lines. The dataset was split at each of these points to produce a list of pulse data segments in which each represented a single pulse waveform. This list was processed in Stage 2.

3.3.3.2 Artefact removal

During the second processing stage individual pulses were originally subjected to simple morphology tests and those with obvious artefacts discarded, for example pulses which had more than one peak and where there was a second peak at more than 30% of the amplitude of the first, and checking that the middle 30% of points had an amplitude of greater than 50% of the peak amplitude.

However, whilst it was simple to produce a test which would eliminate each particular type of distortion seen, for effective results many different tests were needed. In addition, each test made arbitrary assumptions about pulse waveform shape which may be inapplicable to the general population. Consequently, with the exception of testing the overall pulse length, this approach was abandoned and the focus shifted to statistical techniques. Two alternative techniques were found to be reliable:

1. Generating a simple quality metric for each waveform which reflected how much it differed from the mean pulse waveform for the pose. The metric has to be tolerant of small excursions from the mean shape but more heavily penalise large ones. The code was

implemented in a module called the "shape filter" at point A in the program flow in Figure 3-16.

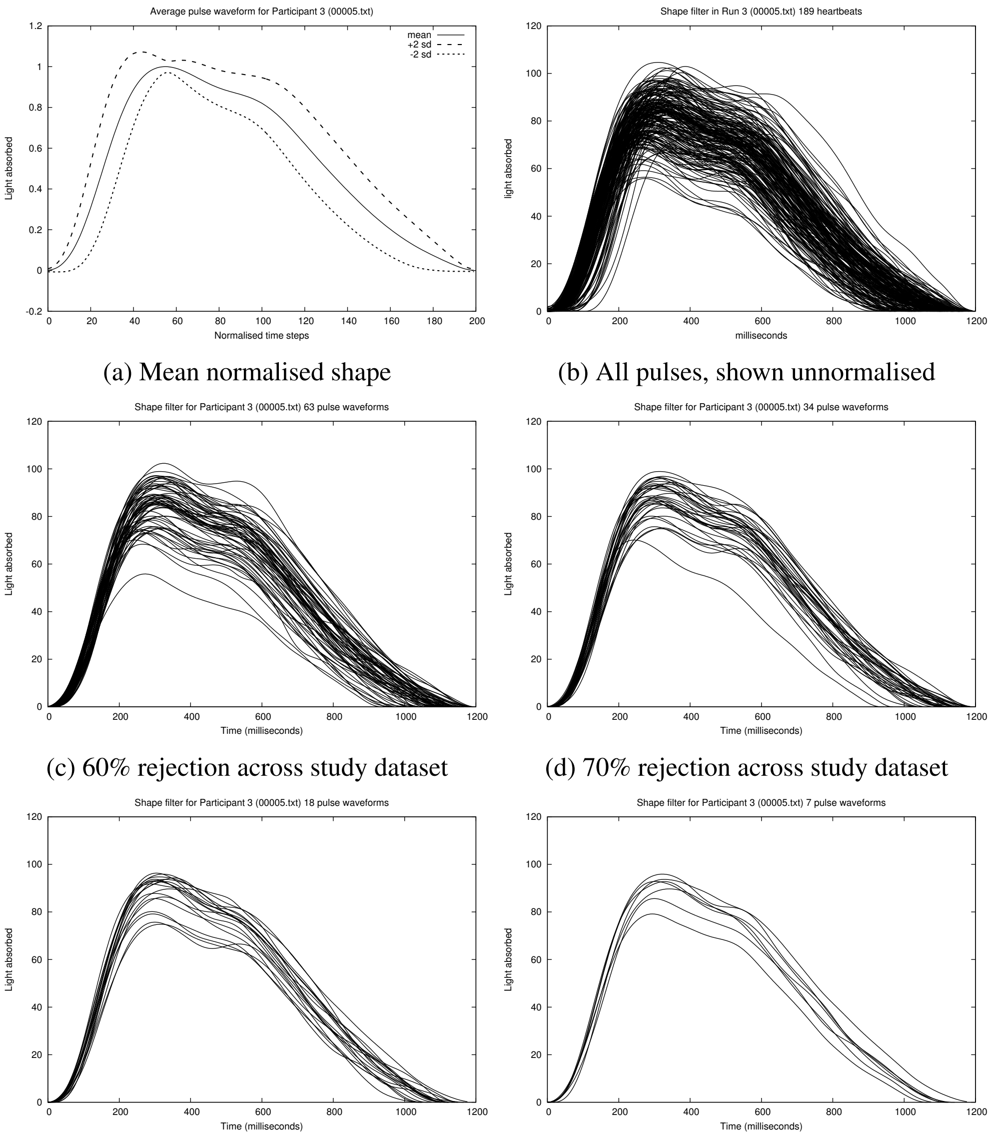
The algorithm adopted was based upon the sum of differences from the mean across all data points after the waveforms had been scaled to a uniform amplitude and width. However, this gave good results to waveforms which had large amplitude but narrow width artefacts. These needed to be excluded because it made the extraction of the pulse rise and decay times problematic since the artefact would provide the peak amplitude. Consequently, the algorithm was modified to raise each difference to an exponent since any large deviation would produce a disproportionately large value:

$$D = \frac{\sum_{i=1}^{N} |(x_i - x_{a_i})^k|}{N} \tag{3.1}$$

Where x_{a_i} is the mean value of each normalised point in the pulse waveform data set for a run, x_i is the corresponding value for the pulse waveform under examination and $N = 200$, the number of points in a normalised pulse curve. Different integer values of k were assessed by examining the borderline curves retained or discarded, and a value of $k = 4$ found to be optimal. The effect of the shape filter is shown in Figure 3-18.

2. Any pulse waveform containing an attribute value outlier was discarded. Outliers were defined as values more than 1.5 times the interquartile range away from either the upper or the lower quartile. The proportion of pulse curves rejected varied slightly with the selection of attributes and the total number of pulse curves rejected increased with the number of attributes used. This was because each attribute produced outliers in slightly different sets of pulse curves. This was implemented by inserting a new step at point B in Figure 3-16 which analysed the attributes extracted by the previous step.

The two algorithms were of similar effectiveness. If the shape filter was configured to reject the same proportion of pulse waveforms as the outlier removal algorithm, then the waveforms it removed were comparable to those rejected by outlier removal. The outlier removal algorithm has the disadvantage that unlike the shape filter its performance is dependent upon which attributes are examined. Nevertheless, the outlier removal algorithm was preferred since it directly addressed noise in the attributes used for pose classification although an evaluation was made of the relative performance of the two algorithms in the classification task which is described in Section 3.3.7.



(a) Mean normalised shape

(b) All pulses, shown unnormalised

(c) 60% rejection across study dataset

(d) 70% rejection across study dataset

(e) 80% rejection across study dataset

(f) 90% rejection across study dataset

Figure 3-18: Effect of the shape filter artefact removal algorithm, Equation 3.1. This was one of the two alternatives techniques to remove grossly distorted pulses. The filter picks the pulses which best match the mean waveform for that participant and pose. In the above figures the filter is set to accept different proportions of pulse waveforms for the entire study dataset. The proportion accepted for a particular participant/pose combination depended upon the pulse shape variation within that combination. In practice rejection values of 10-50% were used.

3.3.4 Results

The number of pulses collected during each run for each pose was less than the 300–400 expected, markedly so in some cases, as shown shown in Table 3.4. It was noticeable that some participants produced a far better pulse signal because of large variations in the amplitude, with the larger amplitude pulse signals producing a waveform less affected by artefacts.

Participant			Pose number										
			Sitting			Standing		Supine					
#	Age	Sex	0	1	2	3	4	5	6	7	8	9	†
1	40	F	268	209	324	328	383	301	260	305	286	286	
2	27	F	255	176	304	112	254	265	182	183	198	164	
3	24	F	366	322	350	343	387	189	158	196	245	273	
4	24	M	350	357	212	320	166	184	254	178	130	324	226
5	26	F	439	358	433	93	417	317	251	151	309	245	
6	56	M	323	201	328	356	324	260	240	155	293	295	
mean			334	271	325	259	322	253	224	195	244	265	226
sd			68	84	71	122	96	56	43	57	69	56	n/a

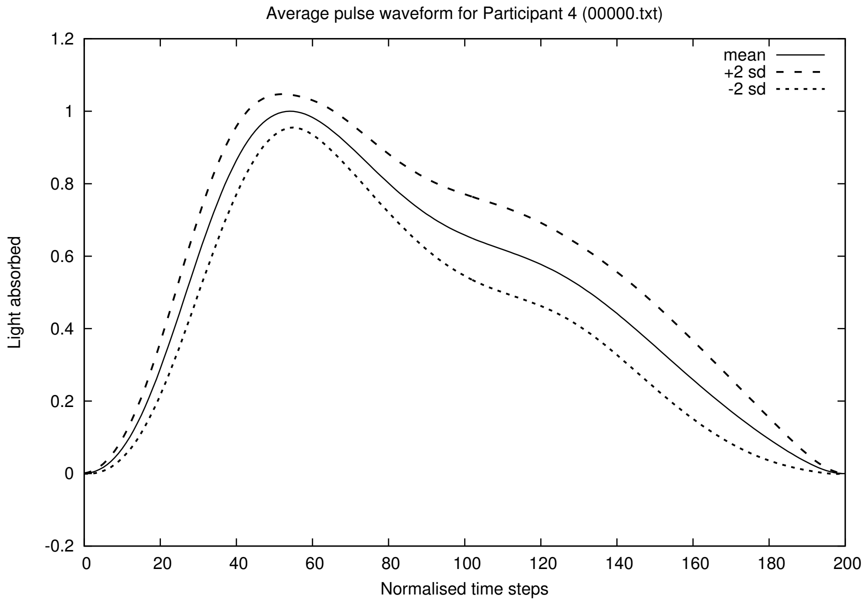
Table 3.4: Number of individual pulse waveforms collected. †The amplifier gain was turned down for poses 5-9 for Participant 4. Pose 5 was repeated to allow a check to be made that the pulse shape was not affected since the gain adjustment mechanism affected the low pass cut-off frequency, as described in Section 3.3.2.1.

An example of the well-documented difference between the pulse shapes of younger people compared to older is shown in Figure 3-19. In younger people there are two distinct peaks but these tend to merge into a single point of inflection as they age. The point of inflection is called the dicrotic notch, derived from Greek *di krotos*, “two beats”. Its position depends on the individual’s height and their arterial wall stiffness. Both affect the propagation delay along the aorta since the height influences its length and arterial stiffness the speed of propagation (Allen, 2007). This suggests that the results may differ between younger and elderly people.

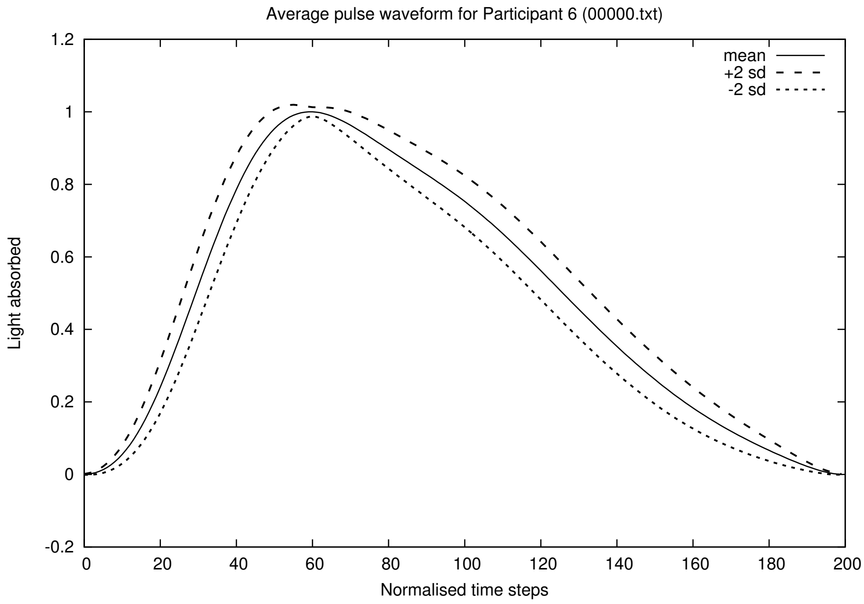
The differences in pulse shapes with pose were consistent with the results of the preparatory work. For example, the mean pulse curves and their difference for test 0, sitting at desk, and test 5, supine, are shown in Figure 3-21, and curves for standing and supine, are shown in Figure 3-22. Participant 2 was the worst for noise and showed a “spikey” curve which was especially apparent whilst the participant was standing.

Differences in pulse waveform shape for the oldest participant are shown in Figure 3-20 and there is probably a continuum of waveforms in between these which represent different arm positions.

Some differences were subtle, for example the gradient of the normalised pulse rise time was reversed in some cases. This may have been because any difference was smaller than the errors in the measurements, or non-existent, or because the normalisation process changed the gradient. The period of the overall pulse when supine is 10-20% larger than when sitting, although the change in the decay showed more consistent differences.



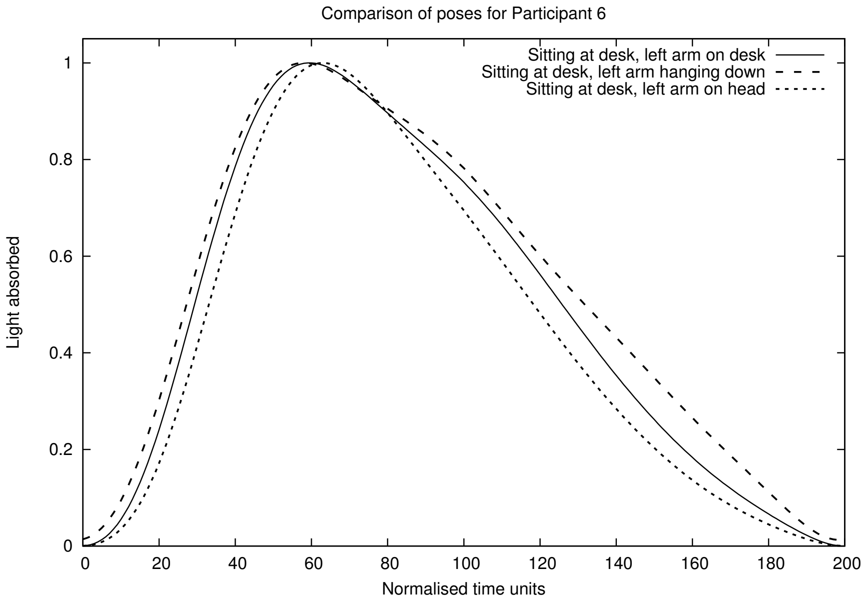
(a) 24 year old



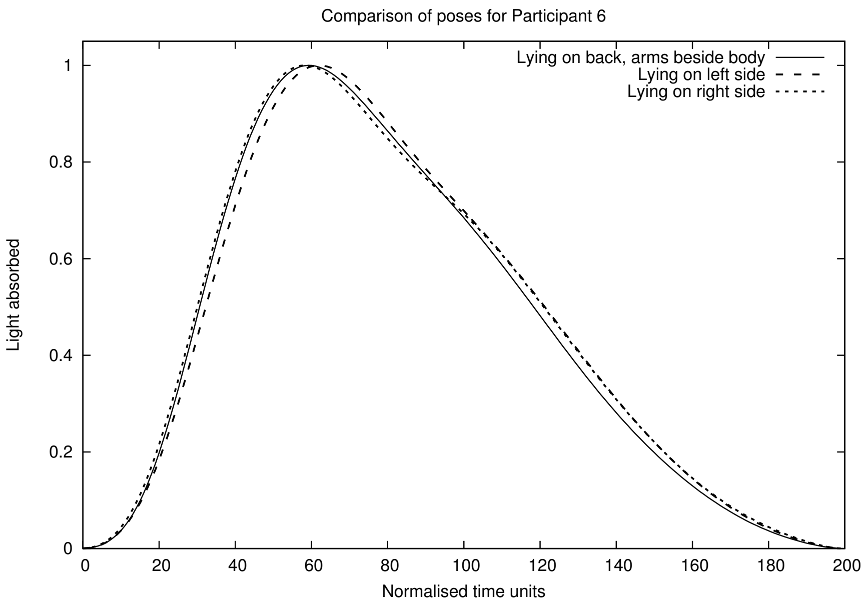
(b) 56 year old

Figure 3-19: Example of pulse shape variation with age – sitting with arms on desk. These means are calculated by taking the mean at each point for all pulse waveforms in the pose scaled to have the same amplitude and width. Pulse waveforms containing artefacts have not been removed in the calculation of these curves (see Section 3.3.3.2).

The arm position had a substantial effect on the waveform shape in the upright body positions. Figure 3-23 compares the pulse waveforms whilst sitting with the arm on the desk and



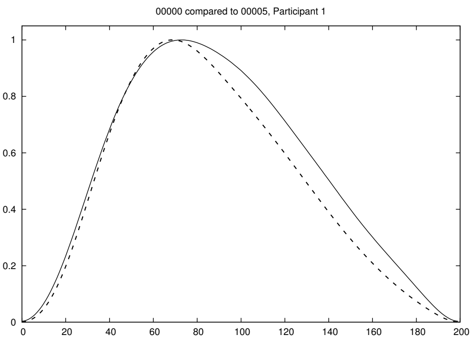
(a) Sitting



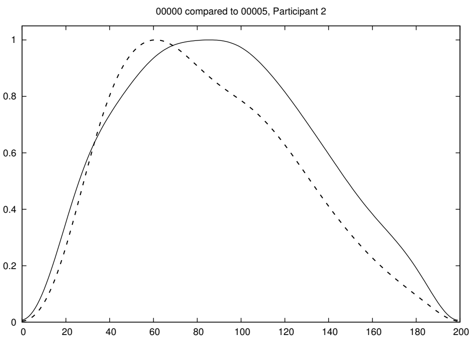
(b) Supine (after Leake et al., 2014)

Figure 3-20: Pulse waveforms showing the effect of different arm positions for the 56 year old participant. Pulse waveforms containing artefacts have not been removed in the calculation of these curves (see Section 3.3.3.2). The arm position had minimal effect in the supine poses.

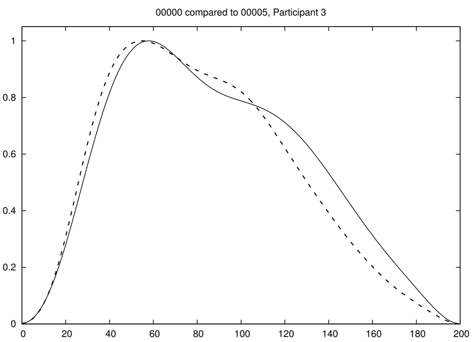
hanging down.



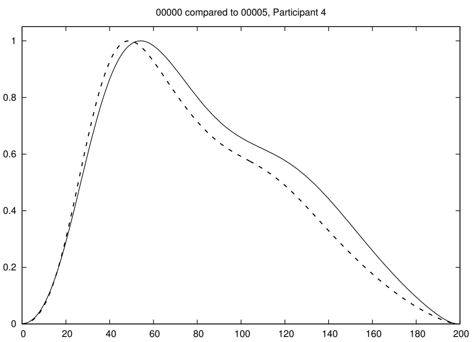
(a) Participant 1 – 40 year old



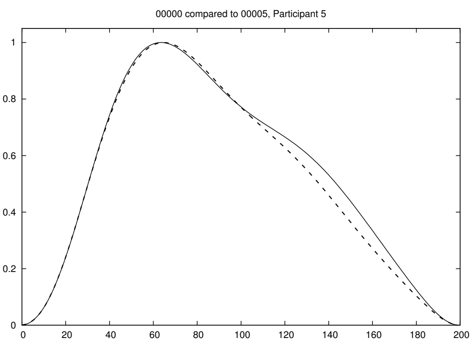
(b) Participant 2 – 27 year old



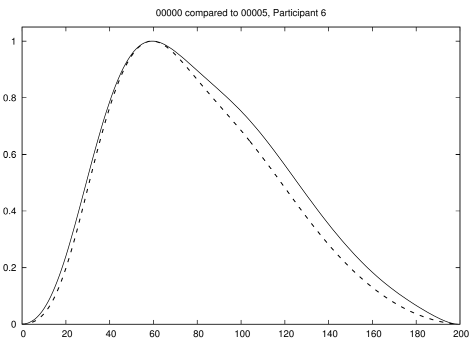
(c) Participant 3 – 24 year old



(d) Participant 4 – 24 year old



(e) Participant 5 – 26 year old

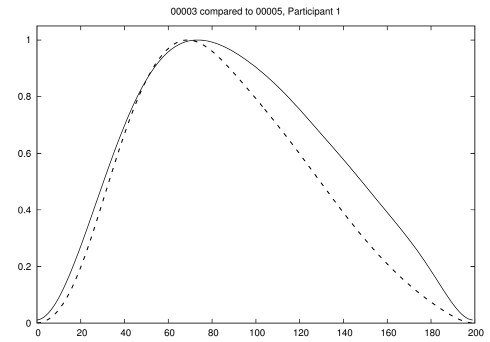


(f) Participant 6 – 56 year old (after Leake et al., 2014)

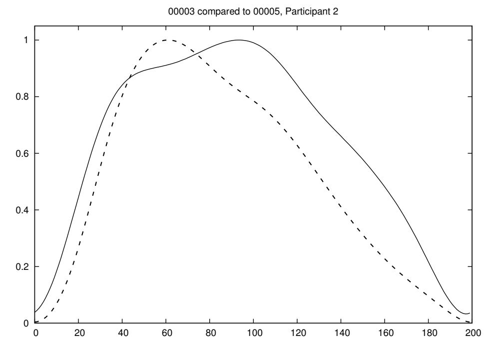
Figure 3-21: Comparison of mean normalised curves for test 0 (sitting, arms on desk) with test 5 (supine on back on floor) for each participant. Test 0 is the solid line. The normalisation makes the period and amplitude of the waveforms uniform. Pulse waveforms containing artefacts have not been removed in the calculation of these curves (see Section 3.3.3.2). The poor quality of Participant 2 data is evident.

3.3.5 Attribute extraction

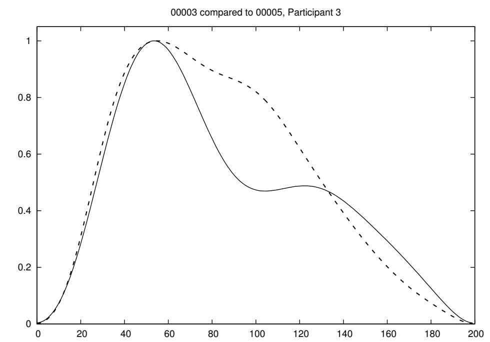
The data stream was split into minima which represented the point where blood had flowed back into the heart, as shown in Figure 3-17. The length and shape of these would be affected



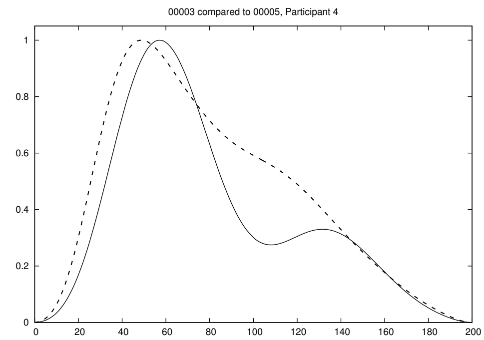
(a) Participant 1 – 40 year old



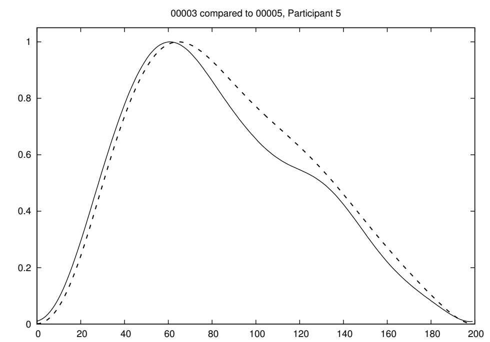
(b) Participant 2 – 27 year old



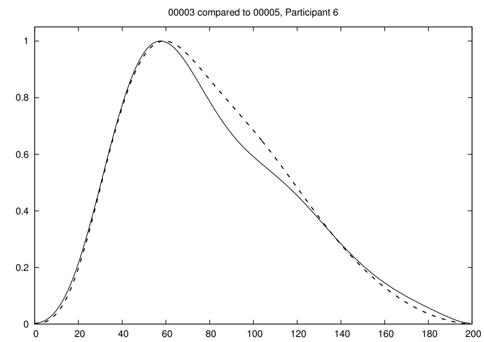
(c) Participant 3 – 24 year old (after Leake et al., 2014)



(d) Participant 4 – 24 year old



(e) Participant 5 – 26 year old

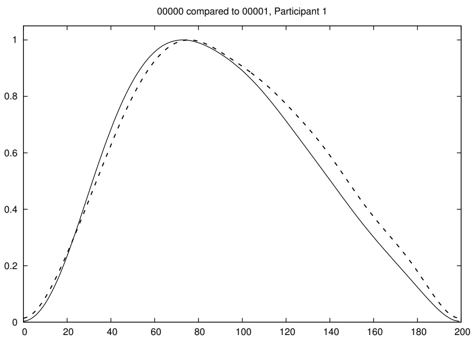


(f) Participant 6 – 56 year old (after Leake et al., 2014)

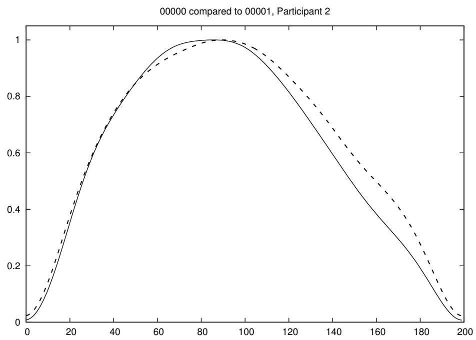
Figure 3-22: Comparison of mean normalised curves for test 3 (standing, arm by side) with test 5 (supine on back on floor) for each participant. Test 3 is the solid line. The normalisation makes the period and amplitude of the waveforms uniform. Pulse waveforms containing artefacts have not been removed in the calculation of these curves (see Section 3.3.3.2).

by the heart rate, since a low heart rate would produce a longer period where not much blood was in the tissue.

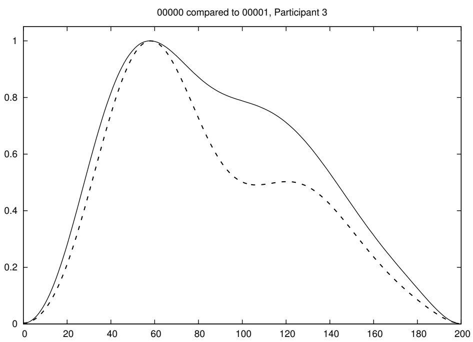
As in the preparatory work, attributes were identified which might discriminate between



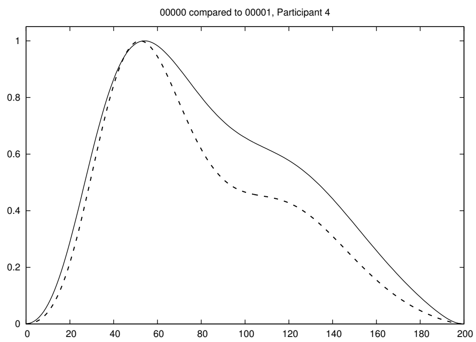
(a) Participant 1 – 40 year old



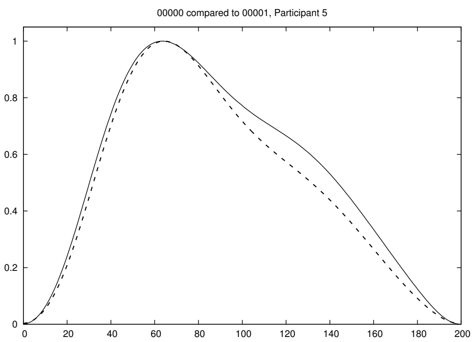
(b) Participant 2 – 27 year old



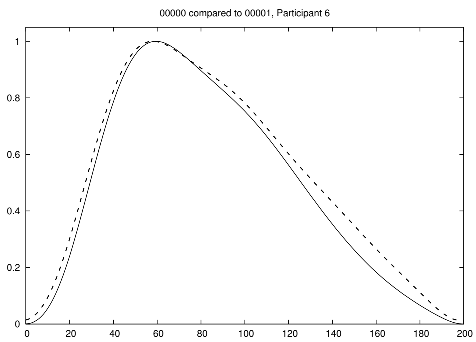
(c) Participant 3 – 24 year old



(d) Participant 4 – 24 year old



(e) Participant 5 – 26 year old



(f) Participant 6 – 56 year old

Figure 3-23: Comparison of mean normalised pulse waveforms for two sitting poses, one with the arms on desk and the second with the left arm hanging down for each participant. This demonstrates the large confounding effect of the position of the left arm wearing the pulse sensor in the upright poses. In particular large changes are seen in the dicrotic notch in the younger participants. Pulse waveforms containing artefacts have not been removed in the calculation of these curves (see Section 3.3.3.2).

the different poses. There are a large number of different measurements which could be made from the data, and the preparatory work served as a useful guide, although the selection of the optimum attributes from the data represents a substantial task. Nine attributes were identified, as shown in Table 3.5.

These were chosen according to the variations seen between different poses. At the same time the total pulse length were disfavoured for a minimal set since the heart rate is known to be higher in someone lying supine, but anxiety or stress will in practice also affect the heart rate.

Symbol	Name	Description
Base measurements		
T_p	Pulse pressure peak length	Time interval B $\rightarrow$ F
T_r	Rise time	Time interval B $\rightarrow$ C
T_d	Decay time	Time interval E $\rightarrow$ F
I_{nd}	Normalised decay integral	Area under E $\rightarrow$ F scaled for a fixed amplitude and total pulse length.
T_t	Total pulse interbeat period	Time interval A $\rightarrow$ G
Derived measurements		
T_r/T_d	Rise/decay time ratio	
T_r/T_p	Rise time/pulse length ratio	
T_d/T_p	Decay time/pulse length ratio	
I_r/I_d	Integral ratio	Ratio of I_r/I_d. Ratio of the area under B $\rightarrow$ C to the area under E $\rightarrow$ F. Equivalent to the ratio of the normalised versions, I_{nr}/I_{nd}

Table 3.5: Attributes extracted from pulse waveform (after Leake et al., 2014)

As in the preparatory work, the presence of noise meant that determining when the pulse rise or decay had finished was problematic since small short duration noise around the maximum or minima could shift this around. The same solution used in the preparatory work was adopted of not looking for the maximum and minimum but values close to it. In this study the lower and upper limits were both increased by 5%, to 15% and 95% limits, as more clearly defining the rise and decay.

3.3.5.1 Pulse rise time and decay time

The preparatory work saw pulse rise and decay curves changing slightly with posture, and in the results for the six participants the decay curve showed more variation than the rise curve.

One challenge was identifying when the pulse starts and ends. The start is when blood starts to enter the tissue being monitored causing an abrupt change in the gradient of the curve. This is difficult to detect reliably because noise and artefacts in the signal and an easier way of standardising the start and end is when signal amplitude passes through a value above the minimum.

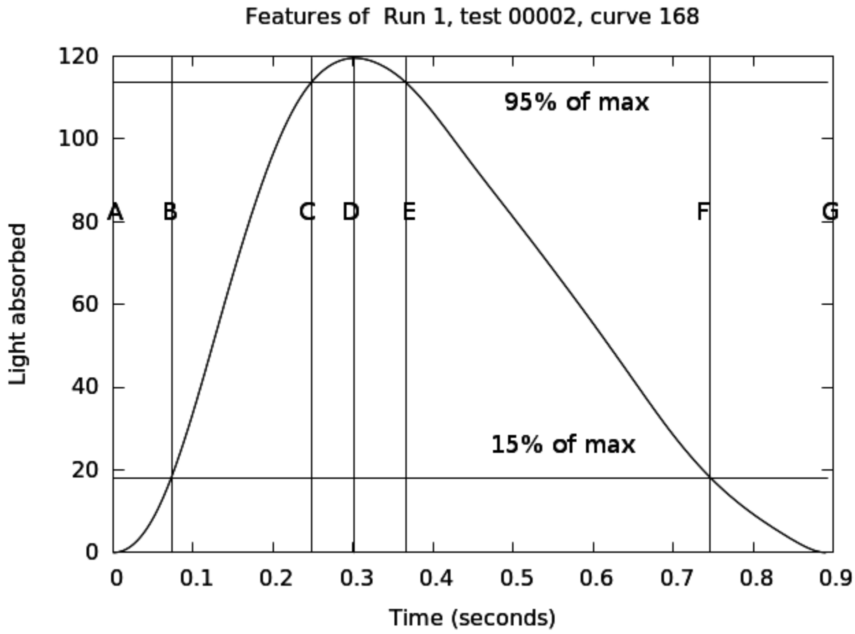


Figure 3-24: Markers for extracting attributes from a pulse waveform. Verticals A and G are the start and end of the pulse, B, C, E and F bound the first and last 15% and 95% values. D is the maximum value.

Whilst this approach worked well for small deviations in the data, it was confused by large artefacts, and was the motivation behind the work described in Section 3.3.3.2. The effect of large artefacts was to extend the rise or decay time, because of small spurious peaks near to the top or bottom of the pulse pressure peak caused the timings of the attributes to be miscalculated as shown in Figure 3-25.

3.3.5.2 Dimensionless values

Dimensionless values formed by taking ratios of measurements with the same units were preferred for identifying characteristics since person-specific differences in one may be offset by similar differences in the other. These included the ratio of the rise time to the decay time, and the ratio of the integrals during these two periods. The ratio of integrals may better reflect reflect bumps in the decay slope. In Table 3.5 these are the derived measurements, T_r/T_d, T_r/T_p, T_d/T_p and I_r/I_d.

3.3.5.3 Pulse length and total period

The pulse length was the period of the pulse pressure peak. It was defined as the time interval from the start of the pulse rise to the end of the pulse decay, as measured using the technique

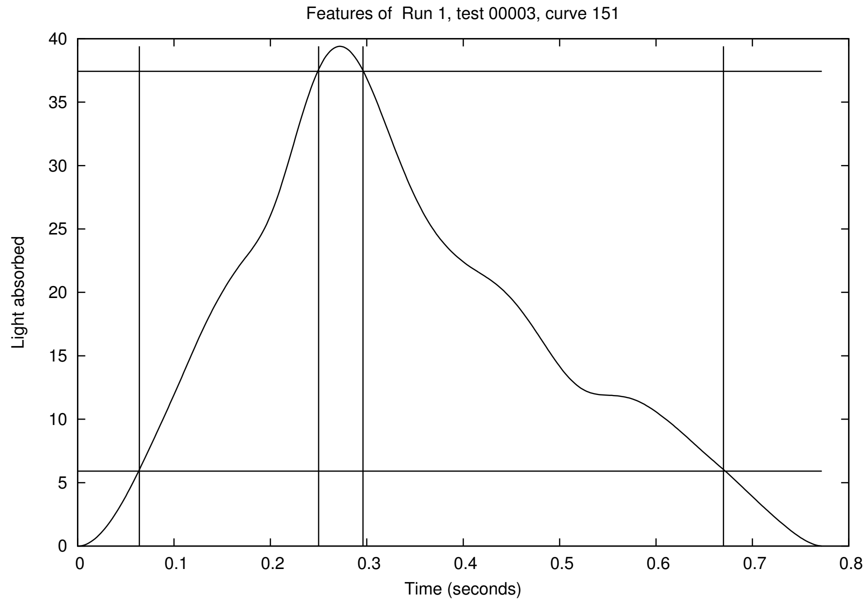


Figure 3-25: Example of a distorted pulse with a large artefact near to the peak. The effect of this artefact is to move the 95% amplitude points closer together, and so overestimating the pulse rise and decay times. The two horizontal lines show the 15% and 95% of peak amplitudes, and the vertical lines delineate the rise time and decay time of the pressure peak.

described above.

The total period was defined as the time period occupied by the pulse as determined by the splitter, i.e. between successive signal minima, and corresponds to the instantaneous heart rate. Heart rate is usually derived from pulse rate by looking for maxima rather than minima, but the result is approximately the same. Heart rate could help to determine body position, although heart rate is strongly affected by the agitation and stress.

3.3.5.4 Analysis of the attributes

The means and standard deviations of the nine attributes for body positions aggregated into sitting, standing and supine for the six participants are given in Table 3.6.

The table shows that the values of the attributes were dependent upon the participants. In addition, whilst there are differences between the mean values of attributes in different poses, they are generally of only one or two standard deviations so there will be an overlap between values. Participant 2 values had larger standard deviations than the other participants, almost certainly because of the level of noise, and particularly for standing poses.

The total pulse period shows a good variation but this is the instantaneous heart rate, and the values recorded in the study may not be representative of someone who is psychologically

Participant	Pose	N pulses	Total period /ms	Length /ms	Rise time /ms	Decay time /ms	Rise/ length ratio	Decay/ length ratio	Rise/ decay ratio	Normalised decay ratio	Integral ratio
1	Sitting	705	911 (81.0)	701 (65.7)	185 (30.8)	398 (53.7)	0.475 (0.107)	0.568 (0.056)	0.265 (0.038)	24.5 (3.28)	0.500 (0.122)
	Standing	623	778 (71.2)	612 (62.0)	161 (31.8)	348 (59.3)	0.479 (0.129)	0.567 (0.072)	0.264 (0.047)	25.7 (4.60)	0.493 (0.156)
	Supine	1258	955 (75.9)	708 (60.4)	192 (18.8)	408 (48.5)	0.475 (0.066)	0.575 (0.035)	0.272 (0.026)	23.3 (2.70)	0.510 (0.084)
2	Sitting	648	939 (90.8)	770 (86.9)	230 (82.7)	390 (78.9)	0.619 (0.284)	0.508 (0.090)	0.296 (0.092)	23.9 (5.58)	0.695 (0.358)
	Standing	322	743 (65.8)	601 (60.4)	173 (65.6)	314 (80.0)	0.617 (0.353)	0.523 (0.128)	0.287 (0.105)	25.2 (7.66)	0.676 (0.447)
	Supine	864	1062 (79.0)	805 (72.6)	198 (47.3)	468 (72.7)	0.440 (0.155)	0.582 (0.080)	0.245 (0.052)	25.1 (4.44)	0.485 (0.200)
3	Sitting	915	822 (65.2)	630 (47.5)	131 (15.5)	417 (33.3)	0.317 (0.047)	0.663 (0.048)	0.208 (0.018)	28.9 (4.68)	0.327 (0.051)
	Standing	633	732 (71.5)	569 (54.9)	115 (14.4)	391 (42.3)	0.298 (0.045)	0.688 (0.039)	0.203 (0.020)	28.2 (4.97)	0.328 (0.053)
	Supine	971	1085 (70.9)	816 (58.8)	156 (15.6)	532 (49.5)	0.296 (0.043)	0.654 (0.057)	0.192 (0.015)	29.7 (3.49)	0.291 (0.055)
4	Sitting	821	765 (43.6)	573 (34.8)	116 (11.3)	392 (25.6)	0.297 (0.037)	0.684 (0.030)	0.202 (0.016)	26.8 (3.15)	0.328 (0.043)
	Standing	434	627 (21.8)	455 (19.9)	98.4 (4.70)	311 (14.6)	0.317 (0.018)	0.683 (0.014)	0.216 (0.008)	21.0 (2.50)	0.426 (0.037)
	Supine	1116	878 (65.6)	620 (40.3)	121 (6.15)	432 (34.3)	0.281 (0.025)	0.696 (0.016)	0.195 (0.013)	24.2 (3.07)	0.331 (0.049)
5	Sitting	1144	672 (30.6)	533 (21.6)	124 (6.64)	334 (15.8)	0.373 (0.025)	0.627 (0.017)	0.233 (0.010)	29.0 (2.26)	0.374 (0.034)
	Standing	456	643 (30.4)	508 (30.7)	117 (7.00)	321 (24.4)	0.366 (0.033)	0.632 (0.025)	0.231 (0.013)	29.6 (3.48)	0.362 (0.046)
	Supine	1138	846 (59.1)	655 (40.2)	148 (11.3)	416 (32.6)	0.357 (0.039)	0.635 (0.024)	0.226 (0.017)	27.7 (1.79)	0.372 (0.044)
6	Sitting	771	903 (41.6)	651 (49.9)	150 (10.3)	409 (47.6)	0.372 (0.049)	0.628 (0.034)	0.232 (0.021)	25.0 (3.21)	0.391 (0.057)
	Standing	603	805 (42.9)	574 (47.8)	129 (12.2)	370 (33.0)	0.350 (0.039)	0.645 (0.033)	0.225 (0.015)	24.5 (2.50)	0.378 (0.035)
	Supine	1171	1042 (63.6)	726 (34.6)	170 (7.39)	456 (26.4)	0.374 (0.024)	0.628 (0.013)	0.234 (0.010)	24.2 (1.30)	0.393 (0.028)

Table 3.6: Mean (Standard deviation) of attributes aggregated by pose. Pulse waveforms containing any attribute outliers were discarded before these values were calculated.

stressed and have an elevated heart rate. The characteristics of the pressure peak, which are its length, rise and decay times, may perhaps be much more useful in a fall detector.

Whilst the overall heart rate can increase to two or three times the resting level, the width of the pressure peak caused by ventricular contraction and relaxation may show less variation. Cardiac muscle contractions do not occur under the direct control of the central nervous system. Instead they are triggered by the action potential generated by the sinoatrial node, a structure located in the right atrium of the heart. It spontaneously generates a continuous series of action potentials at a rate mediated by the autonomous nervous system (Mohrman and Heller, 2010, page 30). These are propagated through the heart, via the atrioventricular node, a structure which delays it until atrial contraction is complete, and then to ventricular muscle, although the propagation speed is also influenced by the autonomous nervous system (Germann and Stanfield, 2005, page 440).

Because of the large overlap between values a single attribute cannot reliably be used to determine pose, especially if the overall length is excluded. For example, Figure 3-26 shows the distribution of pressure peak decay times for the supine poses and the combined sitting and standing poses for the oldest participant. Whilst the average values are different, with a lower value usually seen for the supine poses there is a sufficient amount of overlap that using this attribute alone would be inadequate.

Hence, the determination of pose needs to utilise several attributes, and since the characteristics vary between different people (and these may change over time) a mechanism for tailoring the algorithm to the individual would be needed.

3.3.6 Classifiers

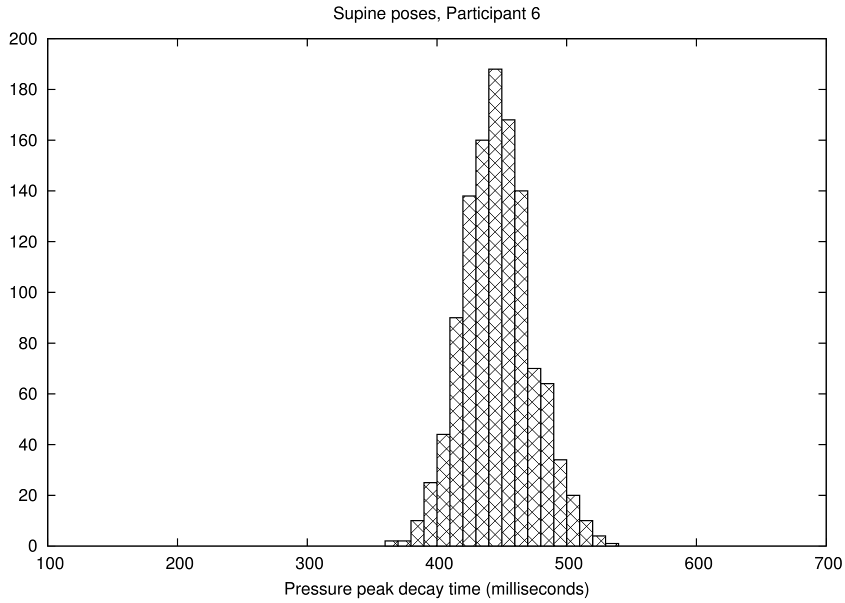
The need to categorise observations into categories based on the similarities and differences between them is a common problem in many disciplines and many techniques have been evolved.

This cross-disciplinary interest means that each discipline brings its own terminology, resulting in an array of synonyms in the subject. For example classification algorithms can be called discriminants or classifiers; the individual data items in the observations are variously called independent variables, input variables, features or attributes; and the target sub-populations are categories or classes. This thesis uses the terms *classifier*, *attribute* and *class*.

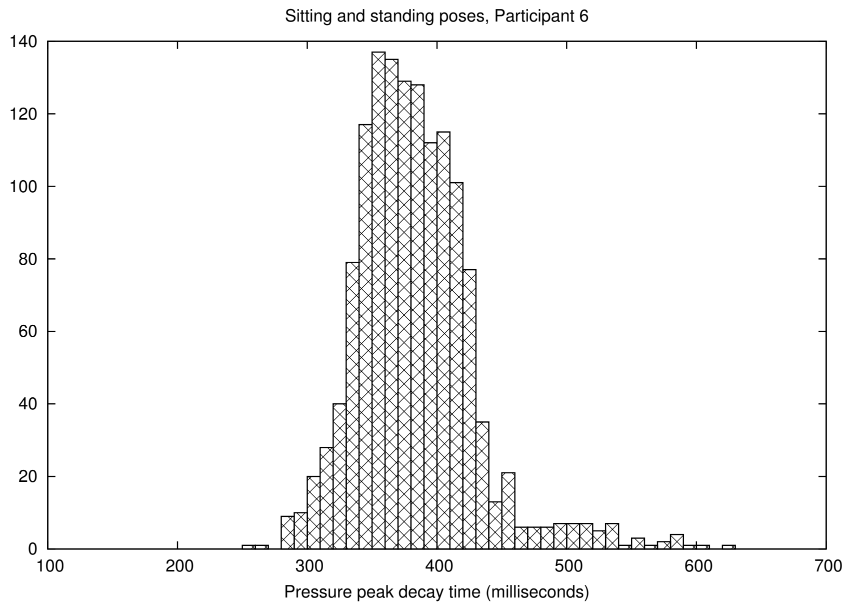
If there is only a single attribute in each observation then the classification task is usually straightforward because each possible attribute value can be mapped directly onto a particular class. However, often classifiers must deal with the situation seen in the pulse shape to pose classification task described above, in which several attributes must be used. Many classifiers operate by reducing multiple attributes to a single score. An example is the linear regression classifier, a simple algorithm which works with continuous attributes by using different weights w_i assigned to each attribute a_i to produce a single overall score x (Witten et al., 2011, page 124–125).

$$x = w_0 + \sum_{i=1}^{N} w_i a_i \tag{3.2}$$

This is a simple example of a linear classifier, where the classification is based upon linear combinations of attributes. If there are only two classes, a *binary classifier*, then the observation is often assigned to one class if x is below a threshold, otherwise assigned to the other.



(a) Supine poses



(b) Combined sitting and standing poses

Figure 3-26: Histograms of the pulse pressure peak decay times for the 56 year old participant in supine, and sitting/standing poses. Whilst the mean values differ there is sufficient overlap for the use of this attribute alone to be insufficient to reliably discriminate between them. Statistical outlier removal using all nine attributes has been run to eliminate pulse waveforms containing outlier attributes so that these histograms represent the data for Participant 6 in Table 3.6.

Another type of linear classifier is the *perceptron*, a binary classifier invented in the 1950s (Rosenblatt, 1958) and the simplest type of artificial neural network, being based on the mathematical formalisation of biological neuron behaviour by McCulloch and Pitts (1943). As Figure 3-27 shows, a perceptron works by multiplying the attributes in the observation by fixed weights and sums them to generate an overall score. The output of the classifier is set to 1 if the sum exceeds a threshold.

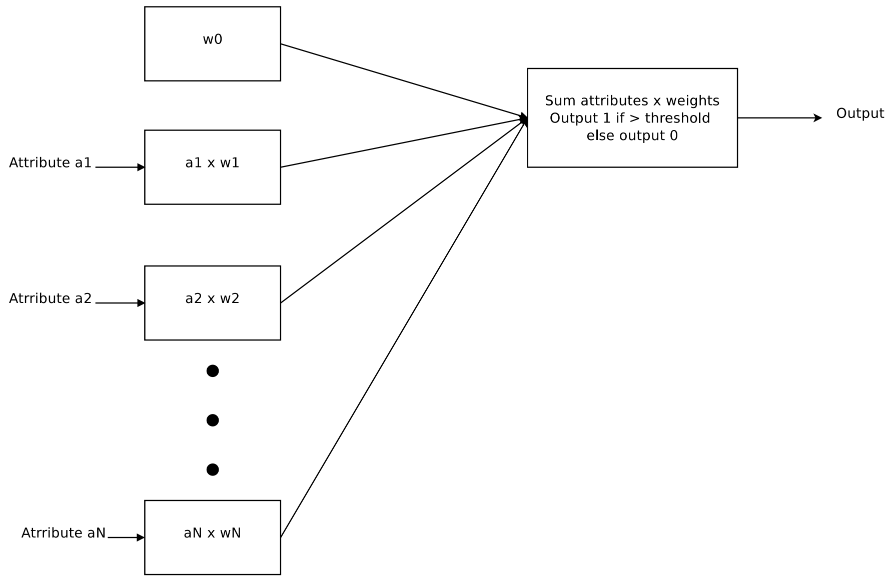


Figure 3-27: A perceptron, which is a type of binary linear classifier. The observation attributes a_i are each multiplied by a weight w_i and the results summed. The input w_0 represents a fixed bias and is not linked to an attribute. Its operation is the same as a linear regression classifier, and described by Equation 3.2. If the sum exceeds a threshold then the perceptron outputs 1 otherwise it outputs 0.

A different approach is used by *Bayes classifiers* which instead incorporate a probability model. This embodies the probabilities of the different classes having the various attribute values. The simplest version is the *Naive Bayes classifier* which assumes that all attributes are independent of each other. Although this is rarely true in practice the Naive Bayes algorithm is very popular because it often outperforms more sophisticated algorithms. The reason is probably that the inter-dependencies between attributes often either cancel each other out or have equal effects across all classes (Zhang and Wang, 2004). A Naive Bayes classifier was used in this study for comparison with the more sophisticated multilayer perceptron, which is described later in this section.

In the simplest case, where attributes have nominal values, each attribute value is assigned a set of probabilities that an observation containing it falls into each of the different classes. There are several strategies for dealing with continuous quantities. These include assigning attribute values to bins corresponding to different probabilities of being in particular classes, or a more complex derivation of probabilities by assuming that the attribute values associated with each class follow Gaussian distributions.

Once the probability model has been constructed a Bayes classifier uses it to classify observations with an algorithm which provides the minimum average risk of misclassification (Haykin, 2009, page 86).

An important feature of any classification algorithm is the ease with which the correct weights, probabilities or other variables within it (usually just known as weights) can be determined to maximise the correct classifications.

If a representative set of observations is available for which the corresponding classifications are known, then a common technique is to iteratively modify the classifier's weights using a feedback mechanism to maximise performance. This is known as *supervised learning*, and permits the classifier to be automatically configured to its operating conditions. In the case of pose determination the classifier could set its weights to suit the physiological responses of the individual fall detector wearer. Efficient supervised learning algorithms which modify the weights to rapidly converge on effective solutions exist for most popular classifiers.

Classifiers are typically evaluated using a set of observations which are split into the *training set*, used to configure the classifier through supervised learning and the *validation set* which is then used to test it. One of the pitfalls of supervised learning is that the classifier algorithm can become highly tuned to the training set, producing excellent classification results but performing much less effectively with new observations which it has not previously been exposed to. This condition is known as *overfitting*, and there are several causes such as the training set being too small, so that the algorithm is not sufficiently generalised.

A common way of testing classifiers which helps to address overfitting as well as providing a better estimate of effectiveness than using single training and validation sets is *10-fold cross validation*. The sample of observations is split randomly into 10 equal sized portions and the classifier run ten times, each time using a different portion as the validation set and the remainder as the training set. The result is the average of the ten runs (Witten et al., 2011, page 152–153). There are several extensions to this technique which include repeating the cross validation multiple times and *stratified cross validation* where steps are taken to ensure that the portions all contain representative proportions of the different classes.

The linear classifiers described at the start of this section are very limited because they require linear boundaries between classes (Witten et al., 2011, page 126–127). Hence, if each observation is plotted by its attributes in N-dimensional space, where N is the number of attributes, then linear classifiers can only discriminate between classes which do not overlap.

Multilayer perceptrons (MLP) are one type of classifier which overcomes this problem. They consist of a network of perceptrons, as shown in Figure 3-28, an example of a three layer perceptron. Despite its name a three layer network contains only two layers of perceptrons because the first layer is composed of nodes which output attribute values. These are then fed into the hidden layer of perceptrons, with each input to each perceptron assigned a weight. The perceptrons in the hidden layer work in the same manner as the single perceptron, producing a 1 if the sum of their inputs exceeds a threshold. The output from the last (or in this case the only) hidden layer feeds the output perceptrons. These function in the same way, producing a 1 if their weighted inputs, from the hidden layer, sum to exceed a threshold. In practice the output is usually from an S-shaped sigmoid function rather than either 0 or 1 because the most popular learning algorithm, backpropagation, requires that the perceptron's transfer function be differentiable (Witten et al., 2011, page 236).

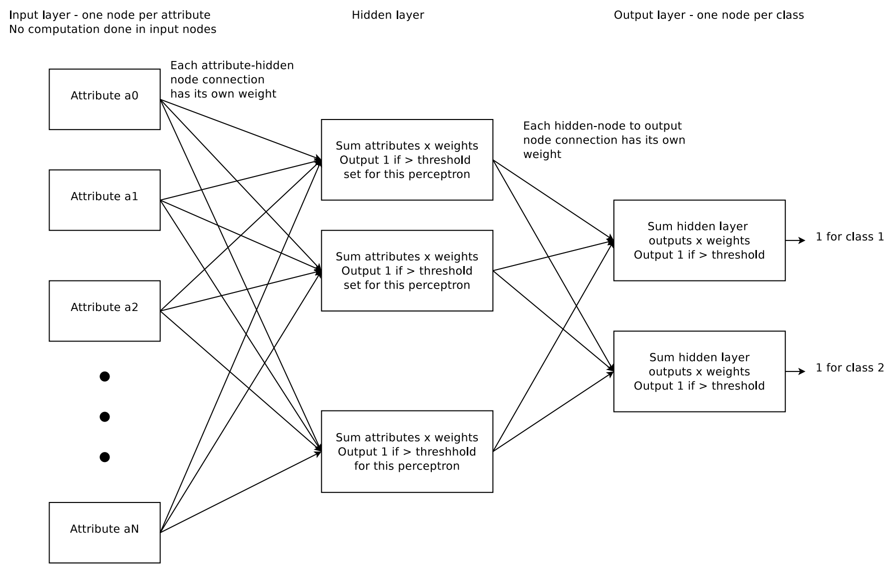


Figure 3-28: A three layer perceptron, an example of a multilayer perceptron. The input layer on the left does not contain any perceptrons but the hidden and output layers do. The hidden layer is named because it does not have connections to either the input or the output and so is "hidden" from the environment. The input layer size is fixed by the number of attributes and the output layer size usually matches the number of classes but the hidden layers may vary in both size and number.

There are many variations on this basic scheme, for example additional hidden layers can deal with complex decision spaces and different number of hidden layer nodes can be used to maximise the accuracy. Whilst there are algorithms which can be used to determine the optimum network structure this is normally done by experimentation (Witten et al., 2011, page 236).

Whilst overfitting can be a problem, artificial neural networks benefit from being straightforward to use, with their self-configuring nature able to automatically handle complex and unexpected relationships between attributes. Their main drawback is that their operation tends to be obscured by the difficulty in understanding the effects of weights and other internal mechanisms (Tu, 1996). In consequence, artificial neural networks are often used for a different purpose to statistical techniques, despite frequently sharing analogous mathematical models (Karlaftis and Vlahogianni, 2011). Whilst statistical modelling builds an understanding of the effects and interrelationships between attributes, neural networks are more suited to quickly producing a working predictive implementation (Karlaftis and Vlahogianni, 2011). This was appropriate for the study because its goal was limited to exploring the viability of using pulse shape for pose determination rather than developing the deeper understanding needed to produce an optimal system.

The multilayer perceptron was selected for this study and the following ones because of its simplicity and ease of use. Whilst MLPs may not produce optimum results without the network topology being tuned, they are sufficiently robust to demonstrate whether determining body position from pulse shape data was viable using this type of approach. No attempt was made to optimise the perceptron network, or explore other optimisation techniques since the goal was to examine the viability of the technique rather than produce a highly optimised system. MLPs have been used before to analyse pulse shape waveforms, for example to detect vascular disease (Allen and Murray, 1993), monitor respiration (Johansson, 2003) and estimate blood pressure (Kurylyak et al., 2013). A conventional three layer perceptron architecture was used with the hidden layer containing one fewer nodes than the input layer.

There are many open source classifiers and neural network libraries available. This study used Weka, from the University of Waikato (Hall et al., 2009), an extensive package written in Java which provides a wide range of classifiers that can be run using either a graphical interface or command line.

3.3.6.1 Success rate

The success rate from a classifier can be misleading because of the effects of chance. With roughly equal numbers of pulses extracted from each of the three poses, a success rate of 33% could be achieved simply by assigning the pulses to pose randomly.

There are better representations of classifier performance than success rate. A common one for binary classifiers is the true positive rate (i.e. ratio of true positives to overall positives) and false positive rate for one of the classes, and when multiple pairs are plotted on a 2-D graph this becomes a *receiver operating characteristic* (ROC) curve (Fawcett, 2006). Although this name dates from their original purpose of characterising radio receiver performance, ROC curves are widely used for evaluating medical diagnostics and elsewhere. Whilst this representation is good for binary classifiers it is less useful when there are more than two classes because the true/false positive rates become points in multi-dimensional space which makes their interpretation and graphing harder (Ben-David, 2008). An alternative metric, originally devised for quantitative psychology (Cohen, 1960), is Cohen's Kappa κ, a scalar between -1 and +1 representing the overall observed classification success rate compensated for chance matches.

$\kappa = 0$ means that the observed success rate matches that achieved by chance, with increasing positive values for rates exceeding chance by larger margins and negative values for rates lower than chance. Figure 3-29 plots the mapping between κ and success rate for a dataset containing equal numbers of pulses from each of the three poses, showing that a 70% success rate corresponds to $\kappa = 0.55$. κ values are conventionally interpreted as the ordinal quality statements listed in Table 3.7.

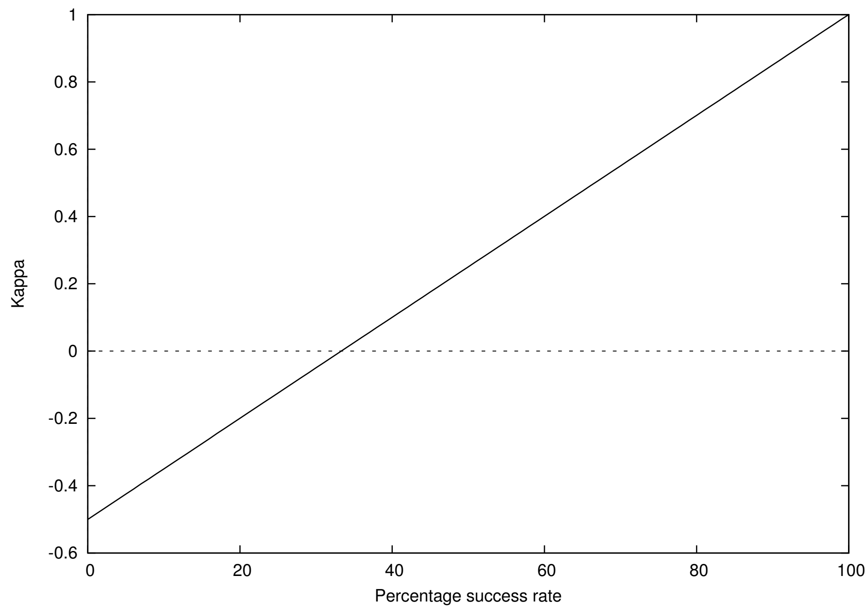


Figure 3-29: Kappa values versus success rate for classifying instances into three classes where the dataset contains the same number of instances of each class. $\kappa = 0$ when the success rate is that expected by chance, 33%. Larger κ values mean that the observed success rate is increasingly above that expected by chance, but negative values occur when the rate is below chance.

3.3.7 Multilayer perceptron classifier

A three layer perceptron implemented using Weka 3.6.10 was used to classify each pulse waveform into one of the three poses. The attributes were those listed in Table 3.5. Three sets of

Kappa κ	Interpretation (Landis and Koch, 1977)	Success rate
<0	"Poor" agreement	$<33\%$
0–0.20	"Slight" agreement	33%–47%
0.21–0.40	"Fair" agreement	47%–60%
0.41–0.60	"Moderate" agreement	61%–73%
0.61–0.80	"Substantial" agreement	74%–87%
0.81–1	"Almost perfect" agreement	88%–100%

Table 3.7: Interpretation of Cohen's Kappa κ. Success rate is corresponding percentage of successful matches for a dataset consisting of three classes of equal size.

attributes were used. The most important was the set of five which did not include the overall pulse period or the width of the pressure peak which were considered to be the most reliable in a fall detector where the heart rate may be abnormal through psychological stress (T_d, T_r, T_r/T_d, I_{nd}, I_r/I_d). The other two were all attributes with the exception of the overall pulse period (T_d, T_r, T_r/T_d, I_{nd}, I_r/I_d, T_d/T_p, T_r/T_p), and finally all attributes (T_d, T_r, T_r/T_d, I_{nd}, I_r/I_d, T_d/T_p, T_r/T_p, P_t).

Weka's default options were used for the multilayer perceptron. These specified a learning rate of 0.3 and a momentum of 0.2 for the backpropagation algorithm, and terminated training after 500 epochs.

It was integrated into the offline analysis software described in Section 3.3.3.1 by adding a step which generated the Weka input attribute-relation file format (.arff) files from the attribute value files generated by the analysis software. To avoid the .arff generation step having to process different files according to whether outlier removal was used or not, the outlier removal module was always run but could be set to a mode where it did nothing other than copy the full set of attribute values to its attribute output files. This allowed the .arff generation step to always read the output files produced by the outlier removal module.

The multilayer perceptron was trained and tested using stratified 10-fold cross-validation separately for each participant and also for all data combined into a single large dataset. The results are summarised in Table 3.8. This shows how each attribute set performed by showing the mean number of instances across the six datasets correctly classified and the corresponding Cohen's Kappa κ value comparing the performance of the neural network with the actual poses.

Since many of the pulses were distorted the outlier rejection scheme was run on the dataset before it was processed by the multilayer perceptron, and the second column shows the proportion of curves rejected by this process.

The multilayer perceptron produced far better results when trained and tested on each of the six individual participant datasets than if they were combined into one large dataset. For example using five attributes (T_d, T_r, T_r/T_d, I_{nd}, I_r/I_d) as attributes produced a mean kappa of 0.74 (Table 3.8 row 1) when each participant dataset was processed independently but only 0.46 when they were combined. This value was even worse than the κ for the worst performing individual dataset, 0.47.

Attributes (count)	Pulse curves removed by outlier removal	Instances mean (sd)	Success mean (sd)	Kappa κ mean (sd)
T_d, T_r, T_r/T_d, I_{nd}, I_r/I_d (5)	8.7%	2490 (313)	83.7% (10.7%)	0.74 (0.17)
As above plus T_p, T_d/T_p, T_r/T_p (8)	9.7%	2461 (318)	86.1% (10.3%)	0.78 (0.17)
As above plus T_t (9)	10.8%	2432 (316)	87.8% (9.9%)	0.81 (0.16)

Table 3.8: Summary of the results for the six participants using the multilayer perception after outlier removal (adapted from Leake et al., 2014, and corrected)

The performance of the multilayer perceptron improved as more attributes were added, as would be expected. The last row of Table 3.8 shows that including the overall heartbeat period T_t provided such a benefit.

A person standing at rest counter-intuitively has a lower heartbeat than someone at rest lying down because the stroke volume of each heartbeat is greater in the person standing, and so the overall blood flow rate is increased. However, this may not be true for someone who has fallen, since they may be agitated and thus have an elevated heart rate. It is not known how the pulse length, T_p, which is the portion of the pulse waveform when the signal is above 15% of its minimum value, is influenced by the overall heartbeat period. Consequently, sets of attributes with and without the pulse length T_p were also evaluated in case T_p was also influenced by the heartbeat period.

The multilayer perceptron results were not strongly influenced by the distorted curve rejection mechanism used. Roughly the same results were seen if 10% of curves with the highest deviation from the mean shape for that pose as for the outlier removal scheme also set to reject 10% of the curves. However, increasing the proportion of curves with high deviations from mean being rejected increased the success rate in determining pose. Not surprisingly, pulses with the most "average" pulse shapes for that particular pose were the best for determining pose. These results are summarised in Table 3.9.

The second column shows the proportion of curves deleted because their deviation D exceeded a threshold. As the amount of rejection was increased then the results improved, which suggests that more "average" pulses are better for judging pose, so that multiple or averaged

Number of attributes used	Proportion of curves rejected	Instances mean (sd)	Success mean (sd)	Kappa κ mean (sd)
5	0%	2727 (331)	80% (9.3%)	0.69 (0.15)
5	10%	2454 (453)	83.5% (10.0%)	0.73 (0.17)
8	10%	2454 (453)	85.5% (9.7%)	0.76 (0.16)
9	10%	2454 (453)	86.8% (9.2%)	0.79 (0.15)
5	20%	2182 (598)	84.7% (9.8%)	0.74 (0.18)
5	30%	1909 (692)	85.8% (9.8%)	0.77 (0.18)
5	50%	1363 (727)	88.6% (9.0%)	0.80 (0.17)

Table 3.9: Effect of discarding different proportions of pulse waveforms which deviated from the mean using the shape filter. The classifier was a multilayer perceptron. The attributes used in the 5, 8 and 9 attribute sets are as defined in column 1 of Table 3.8 (adapted from Leake et al., 2014, and corrected)

Participant	Total pulses	Success pulses	Success	Kappa κ
1	2648	1773	67.0%	0.47
2	1899	1437	75.7%	0.61
3	2570	2142	83.3%	0.74
4	2411	2302	95.5%	0.93
5	2777	2465	88.8%	0.82
6	2633	2417	91.8%	0.87

Table 3.10: Detailed results using the multilayer perceptron with five attributes with outlier removal for each of the six participants.

pulses might be used to more accurately infer pose. The detailed results for each participant using the five attribute outlier removal and perceptron is shown in Table 3.10, and the associated confusion in Table 3.12.

3.3.7.1 Naive Bayes

A multilayer perceptron was used in this study. However, simple machine learning techniques often provide results approaching those of more sophisticated ones, and this is particularly true for the Naive Bayes classifier for reasons described in Section 3.3.6. Table 3.11 shows how Naive Bayesian classification performs following the attribute outlier removal using the same features as used for the classification task for comparison with the multilayer perceptron used elsewhere in this chapter. It is equivalent to Table 3.8 but using Naive Bayesian classification. The results are inferior to those from the multilayer perceptron. All other classifier results tables in this chapter are from the multilayer perceptron, and it was also exclusively used in the later studies, Chapters 4 and 5.

Attributes (count)	Pulse curves removed by outlier removal	Instances mean (sd)	Success mean (sd)	Kappa κ mean (sd)
T_d, T_r, T_r/T_d, I_{nd}, I_r/I_d (5)	8.7%	2490 (313)	76.6% (12.8%)	0.62 (0.22)
As above plus T_p, T_d/T_p, T_r/T_p (8)	9.7%	2461 (318)	77.5% (9.7%)	0.64 (0.17)
As above plus T_t (9)	10.8%	2432 (316)	82.0% (9.6%)	0.71 (0.16)

Table 3.11: Summary of results using Naive Bayesian classification. (All other classifier results tables in this chapter are for the multilayer perceptron).

3.3.8 Published results

The early results were published in Leake et al. (2014), but during a review of the 16,000 lines of Java analysis code as part of the preparation of this thesis, coding errors were identified which affect the published results. The rise time was measured as the 15% amplitude rise start to the 95% amplitude decay start (B $\rightarrow$ E in Figure 3-24). The decay time was measured as the 95% rise end to the 15% decay end (C $\rightarrow$ F). In addition, the rise and decay pulse shape integrals were measured from the start of the pulse to the maximum (A $\rightarrow$ D), and the maximum to the end of the pulse (D $\rightarrow$ G). The corrected figures are presented here, in Tables 3.9 and 3.8, and the corrected source code for carrying out the calculations in Appendix B.

Correcting the rise/decay determination has a very small effect, tending to improve the κ by 0.03, whilst the correction of the integral calculation generally depresses Participant 2 by 0.1 and improves Participant 6 results by 0.1. Participant 2 provided the worst quality data and Participant 6 one of the best, so the cruder determination of the rise and decay integrals may be better for handling spurious peaks. These changes do not materially change the conclusions of Leake et al. (2014) and are further discussed in Section 3.3.9.

3.3.9 Discussion

In this study a sensitive pulse sensor designed for pulse rate measurements was modified so that it could measure the shape of the pulse at the wrist. This was done with six participants in a small range of sitting, standing and supine poses. In all cases differences between the pulse pressure peaks were seen, both in the shape of the waveforms and in the timings of different morphological features and the ratios between them. The use of machine learning techniques to classify the pulse shapes into poses was evaluated using a three layer perceptron. This gave mixed results, ranging between moderate and almost perfect agreement in correctly determining pose using ten-fold stratified cross validation.

Participant 1, N=2648			
	Classified as		
	Sitting	Supine	Standing
Sitting	269	329	124
Supine	222	1006	62
Standing	70	68	498

Participant 2, N=1899			
	Classified as		
	Sitting	Supine	Standing
Sitting	428	174	68
Supine	140	747	10
Standing	60	10	262

Participant 3, N=2570			
	Classified as		
	Sitting	Supine	Standing
Sitting	779	21	141
Supine	23	959	0
Standing	234	9	404

Participant 4, N=2411			
	Classified as		
	Sitting	Supine	Standing
Sitting	785	35	14
Supine	40	1088	2
Standing	16	2	429

Participant 5, N=2777			
	Classified as		
	Sitting	Supine	Standing
Sitting	1077	11	68
Supine	22	1132	2
Standing	206	3	256

Participant 6, N=2633			
	Classified as		
	Sitting	Supine	Standing
Sitting	694	46	64
Supine	38	1144	0
Standing	67	1	579

Table 3.12: Confusion matrix for multilayer perceptron results run with five attributes after outliers have been removed. The counts for correctly classified pulse waveforms are shown underlined. Both standing and supine are most often misclassified as sitting.

The technique achieved a sufficient success rate in discriminating between poses that it would be beneficial in a fall detector. With the minimum five attributes, in Table 3.10, five of the six participants produced κ values corresponding to substantial agreement or better.

However, no allowance was made for the dynamic nature of the arterial baroreceptor response to body movement since several minutes data was collected in each pose, far longer than the time required for the cardiovascular system to return to equilibrium following a large body movement.

Noise and motion artefacts were a serious problem in the study. However, since pulses with the most "average" pulse shapes for the pose performed best for pose determination a real system might produce a composite "average" pulse shape through averaging a sequence of pulses than by trying to analyse each one individually.

The position of the left arm has as significant an effect on the shape as the position of the rest of the body. This may not be a disadvantage since the arm hanging vertically down is unlikely for someone who is prone.

Pulse shape changes as people age. Most of the participants were in their twenties, and the oldest participant was decades younger than the target population for a fall detector and it is not evident from this data how the pulse shape varies in an older population.

The fall detector would have to be trained for each user, because when all of the datasets were combined the classifier performance corresponded to a κ of 0.46, worse than for any individual participant. It is an open question how this would be done since it needs to be as quick and easy as possible and ideally only involve the wearer and their carer. Since genuine falls are so rare, one possibility would be for the carer to inform the base station when the wearer was in a particular pose, and it then activate the pulse sensor to gather classifier training data.

The effect of the corrected attributes is to reduce the performance of pose discrimination slightly but the conclusions of Leake et al. (2014) remain valid despite the small numerical adjustments. These are that the pulse shape is affected by body pose but that it may be difficult to exploit. This is a plausible technique to consider for use in a fall detector, but needs further work to refine and better understand it.

3.4 Limitations of the measurements

The study used only a few participants and with a sensor which was very sensitive to noise and artefacts. The number of poses was limited, especially considering the confounding effect of arm positions and neither the multilayer perceptron nor the feature selection were optimised. The attributes were chosen empirically, and even for the minimal set of five attributes, it is not clear how they may be affected by autonomous nervous system responses triggered by the stress and anxiety accompanying a fall.

3.5 Conclusion

These studies showed that photoplethysmography, using a combination of morphology and timings, can be used to determine body position in a way which could plausibly be used reduce the number of false alarms in a fall detector. This would make it more suitable for someone with dementia unable to cancel false alarms. The pulse sensor would also be able to supply data from which other physiological information could be extracted, which may further improve the efficiency of fall detection.

There are many questions left unanswered by this very limited work – how well it works in older people where the increase in arterial wall stiffness is known to change pulse waveform shape, and how well it works in anxious or distressed people following a fall and what the long term stability of measurements are like.

The practical problems of using pulse shape in a fall detector should not be under-estimated, for example the difficulty in measuring the pulse shape at the wrist and the challenge of coordinating the collection of suitable training data in an assisted living environment. However, this trial showed that the technique deserves further investigation. Two approaches were adopted in the next chapters:

1. Investigate the effect in more people with an improved sensor.
2. Explore the effect in people who are more representative of the target population of the device.

Chapter 4

Body position from pulse shape - a larger study

The results of the first study suggested an extension of the work to examine the effect in a larger sample, which is described in this chapter. This study would provide a greater understanding of the technique and its possible pitfalls.

The pulse sensor was excessively sensitive to movement and a better sensor was needed. Apart from noise and artefact reduction, the measurements would benefit from improved voltage and time resolution to capture more precise pulse shapes. This required changes in both hardware and offline processing. Collecting better quality data was the priority, above that of expending effort producing a sophisticated device which was more than adequate, or examining other areas such as attribute set optimisation.

This chapter details the steps carried out to produce an improved sensor, and then explains the study itself. It discusses the results, which broadly confirmed that determining body pose from pulse shape was viable, but showed that the sensor was still far from adequate to handle the diversity of characteristics of the participants. This shifted the focus to further improvements to the sensor and methodology, which are detailed towards the end of the chapter.

4.1 Apparatus

4.1.1 Design criteria

The physical layout of the LED and photosensor on the commercial hardware (Pulse Sensor Amped) was effective, but other electronics in the first study sensor needed improvement since noise was a serious problem.

The analogue high pass filtering which removed the quasi-DC component and allowed the pulsatile component to be amplified had a settling time of ten seconds or more, so even the slightest movement often lost several pulse waveforms.

The attributes extracted from pulse curves were based on timing information related to peaks and crossing points, and improved time and amplitude resolution would allow more precise attribute measurement. Increasing the sample rate would provide better temporal resolution and the greater oversampling would permit more flexibility in the filtering.

Ambient light flicker and mains interference could be handled by offline digital filters since they provide a much higher roll-off than can be easily attained in hardware, and for this a sample rate which was an integral multiple of 100 Hz was helpful.

A tenfold increase in signal resolution was practical but any more would be lost in noise. The Arduino Uno was replaced by a much smaller Arduino Nano mounted on the wrist to reduce analogue signal cable length but the separate battery box was retained for a reasonable battery life. The voltage was increased from 3 V to 5 V to provide a brighter LED and higher photosensor bias to improve the signal amplitude. Through-hole components were used for convenience of construction, testing and modification. Although this meant that the resulting device would be far larger than a surface mount design, this was not a drawback for an experimental device.

4.1.2 Prototype

Development initially focused upon improving the analogue filtering. The first order high pass filter cut-off frequency was increased from 0.1 Hz to 1.3 Hz which drastically reduced the settling time of tens of seconds. This was achieved by reducing the main high pass filter capacitance and adding a resistor for a more conventional first order high pass filter. The gentle roll-off of the filter meant that frequencies just below the cut-off were still present, but the much lower frequencies of the quasi-DC component were more strongly attenuated. Care was taken to ensure that the phase shift within the region of interest, 1 Hz to 45 Hz, was minimised.

High frequency noise was largely confined to mains and light flicker at 50 Hz and 100 Hz respectively. They presented no risk of aliasing because the analogue to digital converter sampling frequency would be well above 200 samples per second. Nevertheless, a first order low pass filter was added with a cut-off at 2.7 kHz, although in hindsight this was too high to be effective since it was above the Nyquist frequency of the analogue to digital converter. Bode plots comparing the response of the new sensor with the one used in the previous study are shown in Figure 4-1.

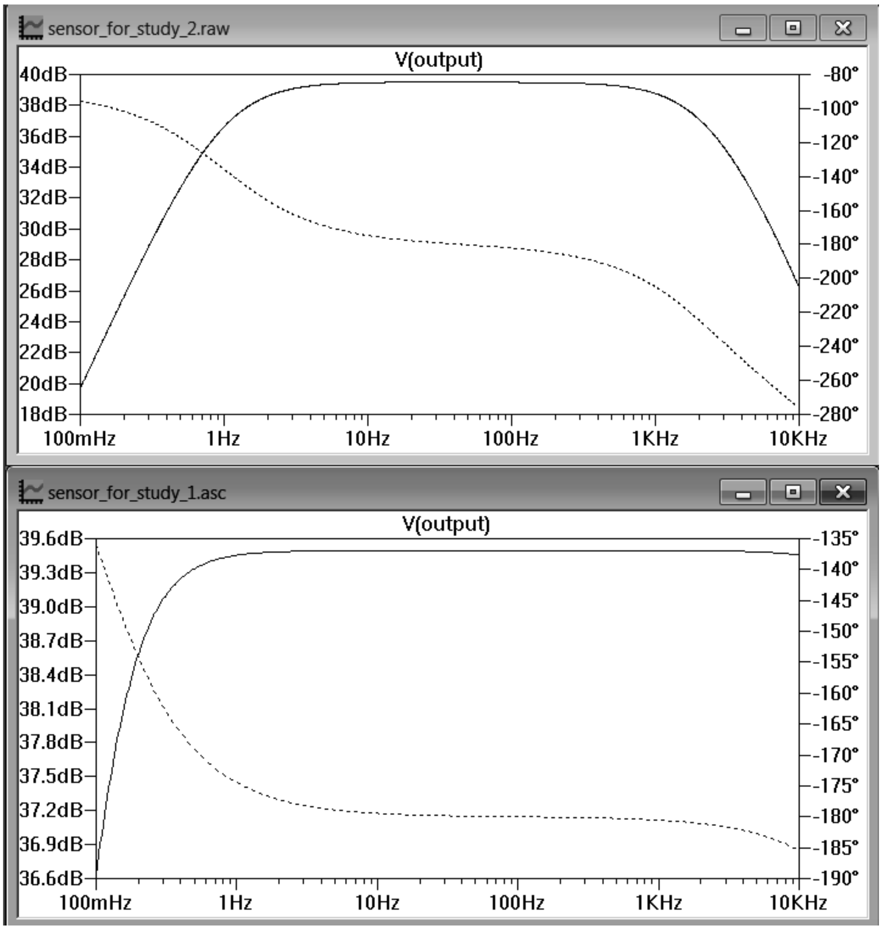


Figure 4-1: Bode plots comparing the simulated responses of the analogue circuit used in this study (top) and the first study (bottom). The solid line is signal attenuation, dotted line is phase shift. The frequencies of interest are 1 Hz to 10 Hz. The high frequency filter cut-off was a compromise between distorting the signal of interest and sufficiently attenuating the higher frequency components of the quasi-DC component.

Experiments showed that the mains frequency interference had a larger amplitude when the device was being worn, probably through capacitive coupling as it was insulated from the wearer. This could have been attenuated by a 50 Hz low pass filter but this would affect the region of interest (1 Hz to 10 Hz). Other alternatives were also considered but in the final analysis a fourth order digital high pass filter did a far more effective job without adding unnecessary complications.

The built-in 11 bit ADC in the Arduino's atMega microcontroller was discarded in favour of a higher precision discrete device which would also reduce noise. A device utilising SPI-like (serial peripheral interface) communication with the Arduino was preferred since this would be easy to interface to the Arduino and minimised the number of connections. This type of data interface typically has a data out line carrying serial data from the ADC to the microcontroller, a clock (i.e. a continuous square wave signal provided for synchronisation purposes) provided by the microcontroller to the ADC and a device select line used by the microcontroller to enable the ADC.

An ADS8320 16 bit ADC (Texas Instruments, Inc, 2007) was selected, although it was not without its problems – for example it proved very sensitive to electrical noise. This occurred because the conversion process required the Arduino to drive the clock lines on the ADC which caused large ripples on the Arduino power supply. The solution adopted was as before, to use a separate battery for the pulse sensor circuit and ADC. The Arduino SPI interface was implemented using a software library rather than the hardware SPI support included in the AVR microprocessor, because it allowed finer control of the data clock frequency. A block diagram of the prototype is shown in Figure 4-2, and the circuit schematic is shown in Figure 4-4.

As before the option of limited control of the amplifier gain was provided by jumpers to select resistances to deal with exceptionally large pulse amplitudes saturating the amplifier. However, this carried the penalty of changing the frequency response of the sensor. Consequently, although the ability to change this resistance was carried over to the next version of the pulse sensor (which was the one used for data collection in the study), a fixed 15 kΩ resistance was used because of the concerns about the effect on the frequency response.

Varying the R3 feedback resister on the U2 operational amplifier would have been preferable but it was felt important to minimise the amount of cabling on the Amped sensor circuit board so that it was mobile enough to closely align with the surface of the skin and this would have required two more wires to it.

Cross-talk on the pulse sensor analogue output from the ADC clock signal was seen during breadboard prototyping, and the layout of the printed circuit board was adjusted to move the high frequency ADC lines as far away from the pulse sensor analogue signals as possible. Other measures taken to reduce interference were to ensure that there were no ground loops in the implementation of the circuit, smoothing capacitors on some of the ADC power connections, locating the Arduino board (where high frequencies would be present) several centimetres from the filtering board and screening the cable between the two.

The prototype had extensive screening of signal cables between the Arduino and the analogue board, and on the battery power supply. This was to protect the power supply circuit from noise spikes induced by the SPI circuit operation and the Arduino, which meant that the power supply cable was screened in the region of the Arduino and the SPI circuit was screened to reduce its emissions.

A small dip in the analogue pulse signal was seen when the Arduino read out the ADC, due to the pulse sensor's op-amp drawing more current as it charged the ADC sampling capacitors.

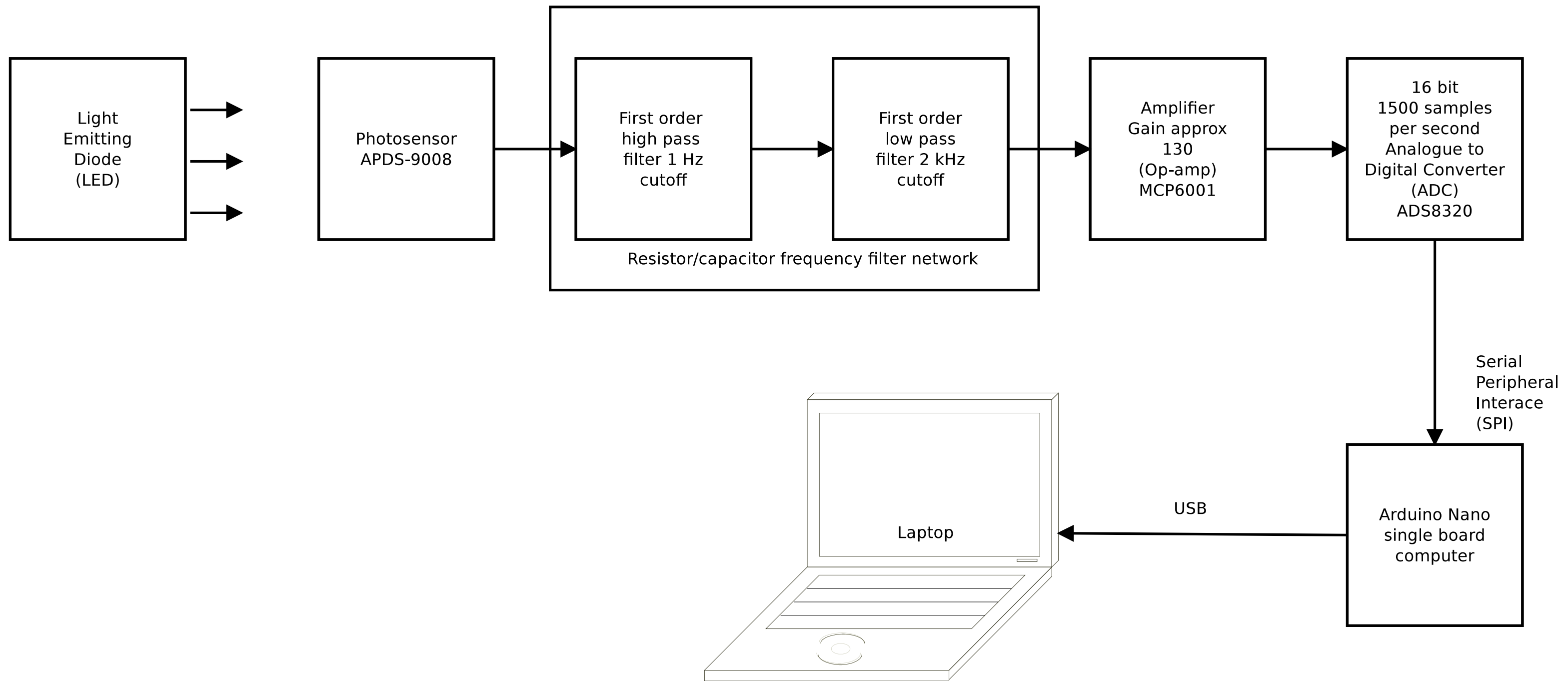
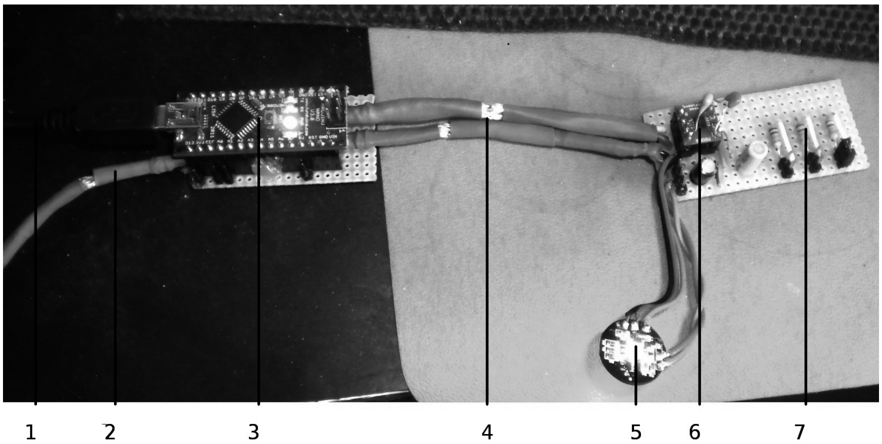


Figure 4-2: Block diagram of the prototype for the improved green light pulse sensor showing the data flow. The LED light scattered back from the skin is received by the photosensor, filtered to remove much of the quasi-DC component, amplified, inverted, digitised and transmitted to the laptop.

Fitting a large, 1.8 mF, capacitor in parallel with the battery considerably reduced this problem. A photograph of the prototype device is shown in Figure 4-3.



1. USB cable to laptop
2. Screened cable to battery box
3. Arduino Nano
4. Screened cables
5. Modified Pulse Sensor Amped
6. ADC on analogue board
7. Analogue filter with selectable resistors

Figure 4-3: The first prototype improved green light pulse sensor.

4.1.3 Second version

A second version of the device was constructed because whilst the analogue electronics were now adequate noise was still seen in the digitised signal. Three copies of this version were eventually constructed: one for wrist measurements, one with the green LED replaced with red (see Section 4.12), and a third with a different physical layout for fingertip measurements. A block diagram of the refined circuit is shown in Figure 4-6.

The clumsy jumper arrangement for selecting the amplifier gain was replaced with a pair of headers into which a resistor soldered to a jumper could be connected. However, concerns about the effect on high pass frequency cut-off meant that a single fixed value of 15 kΩ was always used.

The new version replaced the ADS8320 analogue to digital converter with an MCP3301-BI/P differential ADC (Microchip Technology Inc, 2011). Although this had 13 bits resolution rather than 16, it was not a major drawback since the bottom bits of the ADS8320 were largely buried in noise and this still represented an 8-fold improvement over the Arduino's built-in ADC. The digital board was again separated from the analogue board to limit the noise on the analogue board, and to make the sensor more manageable when worn.

In contrast to the ADS8320 ADC, the MCP3301 produces a signed output which is zero if the signal voltage is equal to the reference voltage and at its maximum if the signal voltage is twice the reference voltage. Consequently, the reference voltage needs to be halfway between the positive and negative rail. A voltage divider was rejected because of the adverse effects of noise in favour of an MCP1525 2.5 V reference source.

The Arduino ground and signal lines were electrically isolated from the ADC and the analogue board using additional devices since the MCP3301 does not internally isolate the SPI signals from its analogue circuitry. This proved very beneficial as it eliminated the connection between the Arduino's USB ground and the battery negative and so reduced the level of noise seen on the battery supply powering the front end electronics.

Three single channel Si8711-CC isolators were used rather than a single three channel isolator as it allowed the board to be debugged more easily as channels could be enabled or disabled individually by inserting or removing the chips. The isolators had inverted open drain outputs – at 0 V when a logic 1 (5 V) was applied to its input, and tri-stated – an open circuit – when a logic 0 (0 V) was applied. The isolator chip packages' built-in 20 kΩ resistors were inadequate to sufficiently rapidly overcome the Arduino digital input pin capacitances even at 100 kHz when seen on an oscilloscope. Consequently, 680 Ω pull-up resistors were used to pull the tri-stated outputs to 5 V with an acceptably fast signal edge at 500 kHz. A schematic of the digital board is shown in Figure 4-8.

The inversion of the digital signals by the isolators was corrected in the Arduino software rather than with hardware inverters, for example by inverting the value used to set the pin driving the ADC chip select. Data from the MCP3301 is valid on the falling edge of the clock, the inversion of the clock signal by the digital isolator meant that the Arduino needed to read the data on the following rising edge instead.

The ADC data output to the isolator had a 10 kΩ pull-down resistor on it to prevent it from floating and potentially picking up noise when the ADC was inactive. The earthed braided screening of the prototype was discarded as it made the cables too bulky and experiments using screened multicore cable did not show any benefit. Although V_{CC} and ground cables were twisted together to reduce common mode noise, the general strategy adopted was not to be overly concerned about mains or ambient light flicker interference, since this could be removed by offline digital filtering.

The data rate of the original device was limited by the 115200 baud rate of the serial link to the laptop. It was impractical to use a higher baud rate because of lack of support on the the laptop, and switching to a faster physical medium such as Ethernet would have required additional hardware. Instead, the data rate was increased by reducing the data record size by

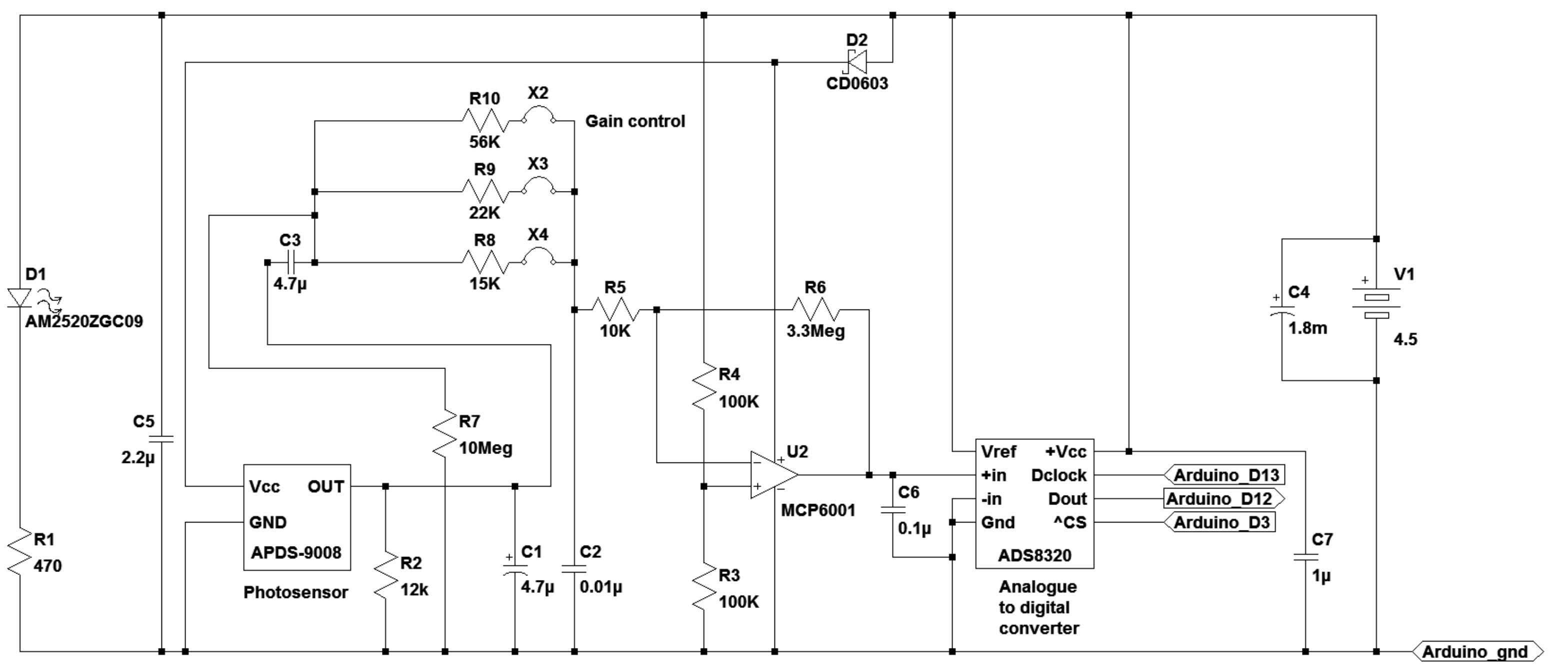


Figure 4-4: Schematic of the first prototype of the improved green light pulse sensor (see Figure 4-3). This was not used for data taking with participants but informed the design of the sensor which was. It used a mix of components on the original Amped sensor and new components on mezzanine boards. It is best understood with reference to the block diagram in Figure 4-2. Licensed under the TAPR Open Hardware License.

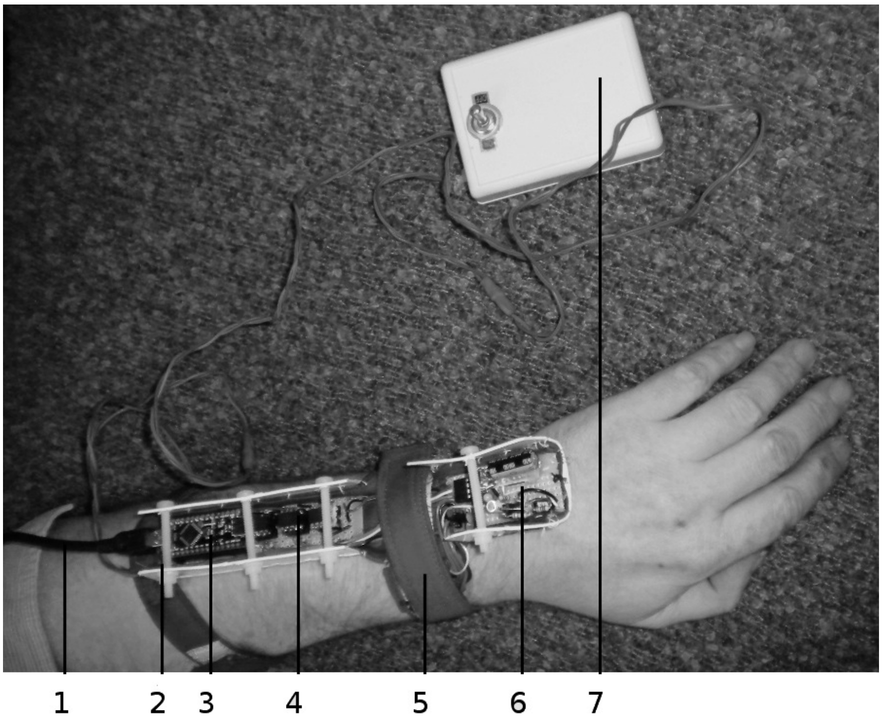


Figure 4-5: Second version of the improved green light pulse sensor, before jumper controlling LED gain was added. The device was usually twisted slightly to the left so that the electronics are on the edge of the arm and the pulse sensor lies on the top.

1. USB cable to laptop
2. Plastic fairing for digital board
3. Arduino Nano
4. Opto-isolator
5. Modified Pulse Sensor Amped
6. Analogue board and ADC
7. Battery box

changing the representation of the timestamp and data value fields from ASCII to binary, which allowed a maximum data rate of about 1750 samples per second.

Length /bytes	Description
1	Character 'P' marking start of datum
2	Least significant bytes of microsecond timestamp
2	13-bit signed pulse amplitude datum. Top three bits are as read from ADC by 16 bit read cycle and unused.
1	Cyclic redundancy check byte (CRC-8-ATM)

Table 4.1: Format of each pulse sensor reading transmitted over USB from the Arduino to the laptop.

The new format is shown in Table 4.1. Timestamps were generated using the Arduino `micros()` function, which overflows and rolls over to zero after 2^{32} microseconds, about 70 minutes. This rollover was irrelevant to the sensor readout firmware since it only transmitted the bottom two bytes of the timestamp, and consequently was insensitive to the value of the upper six bytes. Overflows were avoided on the laptop by representing the timestamps as 64 bit Java longs as 32 bit signed integers would overflow after 35 minutes. Although individual test files were only five minutes long the data recording program normally ran throughout the entire trial which would take an hour.

A CRC-8-ATM (ITU-T, 1999) checksum byte was included both for burst error detection and to help the laptop data receiver program to synchronise with the transmitted data. It used a lookup table generated by an open source tool, Pycrc (Pircher, 2012). Whilst the USB protocol itself incorporates a 16-bit checksum inspection of the libftdi1 library source code used by Linux to read the Arduino's FT232RL serial-USB chip showed that the library ignores USB checksum errors. By confirmation several CRC-8 checksum errors were seen by the data collection program during testing which were traced to a faulty USB cable connector. Half a dozen more errors were observed during data collection with one participant and were handled by flagging them in the data file so that the offline processing software could replace offending data values with those of the previous sample. With the high data rate losing one or two values in a pulse waveform was inconsequential.

The checksum was also used to synchronise the data recording program on the laptop with the Arduino when the program was started by discarding all data until a valid checksum was received.

The new data format was implemented in the receiver software by replacing the front end processing which converted the datastream into timestamp/datum pair structures. The laptop verified the checksum and sign extended the 13 bit datum to 16 bits.

The Arduino transmitted 1500 samples per second, using the code listed in Section A.2. The microsecond timestamp resolution facilitated the higher data rate since the previous millisecond resolution was inadequate above 1000 samples per second. The Arduino read out the ADC using its hardware SPI, with a clock speed of 500 kHz which meant the readout took 32 µs. This was the highest practical speed, selected because of noise at higher clock speeds, and to keep battery power consumption down as faster clocking would have required lower value pull-up resistors on the isolators.

4.1.4 Testing

The original Arduino Nano 3.0 clone device proved troublesome as the serial port would often fail to be visible to the laptop (although this was never an issue with the desktop computer on which the software was originally developed). The most likely cause was that the TEST pin on the FTDI USB to RS232 converter chip FT232RL was left floating, a hardware bug in the original Nano design (Keinonen, 2014). Replacing the clone with one from a different manufacturer, Sainsmart, fixed the problem, as did grounding the TEST pin by soldering it to the adjacent AGND pin.

Sainsmart Arduino boards have exceptionally bright diagnostic LEDs and these were darkened with paint to eliminate any risk of affecting the photosensor, particularly as the serial port transmit and receive LEDs were synchronised with data readout cycles and might have caused problems which would be difficult to debug.

The actual range of values observed during testing was -4095 to just over +2000, rather than the ADC's full range of -4096 to +4095. The problem was traced to the batteries only delivering 4 V to the board because of ohmic losses. The 2.5 V reference source defined the ADC input voltage range as 0 V to 5 V, but the input voltage (and the ADC power) never exceeded 4 V.

The problem was corrected by replacing the three 1.5 V AA batteries powering the system with a 9 V PP3 battery stepped down to 5 V by a Texas Instruments A7805C linear regulator. This increased the upper limit of ADC output to about 3750, corresponding to about 96% of the 0 V to 5 V range, probably largely due to the forward voltage drop of the op-amp's protective Schottky diode D2. In the original pulse sensor Amped design this diode prevented the sensor from being damaged if accidentally reverse biased.

A linear regulator was selected over the more power efficient switched mode type because of its better noise characteristics. As the pulse sensor circuit drew 14 mA at 5 V, the voltage regulator would dissipate 60 mW, a negligible amount of heat. It was mounted on a mezzanine board on the analogue filter board where it had the additional benefit of mitigating any noise picked up by the battery cable.

As with the first prototype, a small voltage drop was seen in the analogue output at the moment when it was being digitised, and the same solution of a 1.8 mF reservoir capacitor across the power rails substantially reduced this drop. However, this meant that the regulator output would be held at a higher voltage than the input when the battery was turned off, since the capacitor took several seconds to approach discharge. Although the 5 V output voltage should never exceed the 7 V needed to damage the regulator a 1N4001 shunt diode was added to protect it.

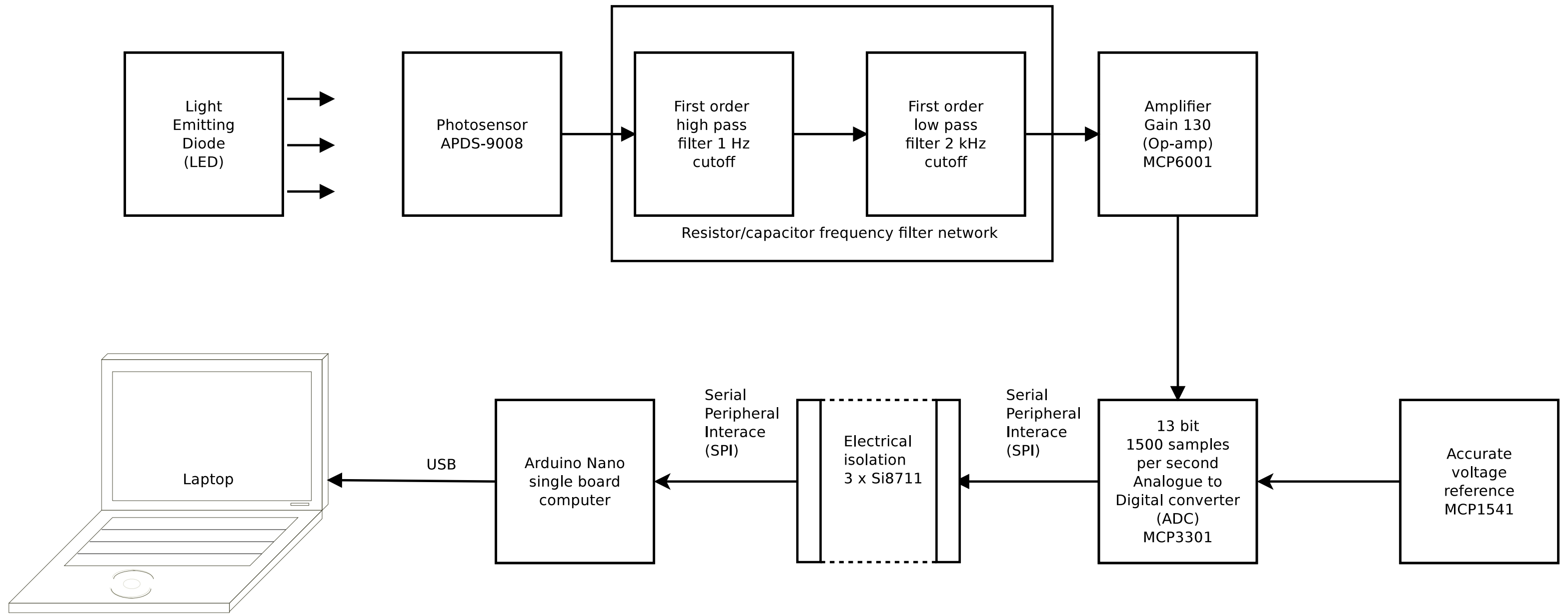


Figure 4-6: Block diagram of the final circuit for the pulse sensor showing the data flow. The LED light scattered back from the skin is received by the photosensor, filtered to remove much of the quasi-DC component, amplified, inverted, digitised and transmitted to the laptop. The Arduino and laptop are electrically isolated from the rest of the circuit.

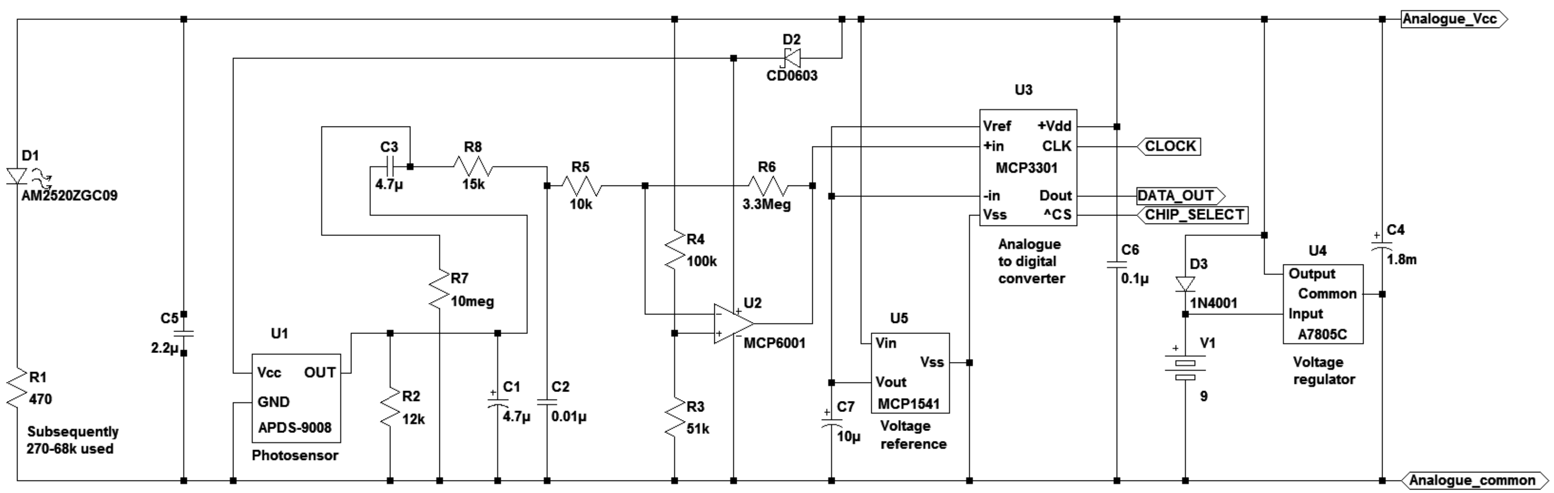


Figure 4-7: Final circuit for analogue portion of the pulse sensor, including modifications to the Pulse Sensor Amped. The schematic is best understood with reference to Figure 4-6. Licensed under the TAPR Open Hardware License.

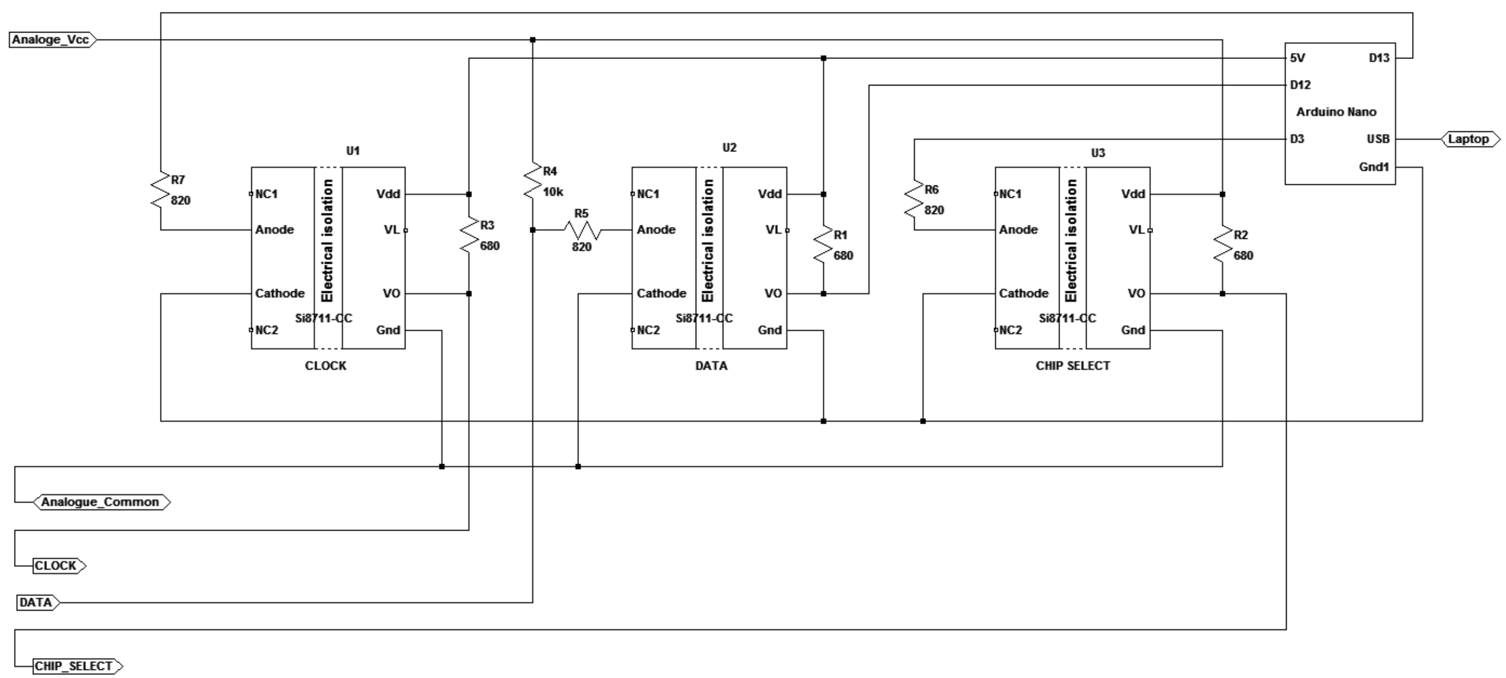


Figure 4-8: Pulse shape sensor digital board schematic. The three Si8711-CC digital isolators provide electrical isolation between the analogue filter board and the Arduino signal lines, but allow digital communication. The Arduino formats the data read from the analogue filter board, adds a checksum, and sends it to the laptop over a USB connection. The Arduino is powered from the laptop's USB connection. Licensed under the TAPR Open Hardware License.

4.1.5 Analogue filtering

Concern about small changes in cut-off frequency and phase as different gain control resistors were used led to the decision to use the same gain as far as possible for all participants. The original jumper arrangement was modified so that the 200 kΩ resistor was replaced by 0 Ω to allow a wider range of resistances to be explored. At the same time jumpers were made up with incorporated series resistances to allow them to be more easily varied. The 0.1 µF capacitor C2 was problematic because LTSpice (an analogue circuit simulation program) showed it to be the cause of the frequency response being dependent upon the value of R8. However, simulation also showed that removing it dramatically increased the amount of higher frequency noise and so it was left in place.

R3 and R4 in Figure 4-7 act as a voltage divider to set the steady state output voltage of the op-amp, and in the unmodified Amped device each had values of 100 kΩ to set the quiescent voltage to $\frac{V_{cc} \times R3}{R3+R4} = 2.5\,\mathrm{V}$. However, the output voltage from the op-amp when it was being driven by a pulse signal had a minimum value of about 3.7 V, so the R3 biasing resistor on the sensor board was reduced from 100 kΩ to about 50 kΩ to pull the quiescent voltage down to avoid large amplitude pulses approaching 5 V and being clipped. In two devices this was achieved by stacking a second 100 kΩ surface mount resistor on top of the original one, in parallel with it, and in the third by replacing the original resistor with a 51 kΩ one.

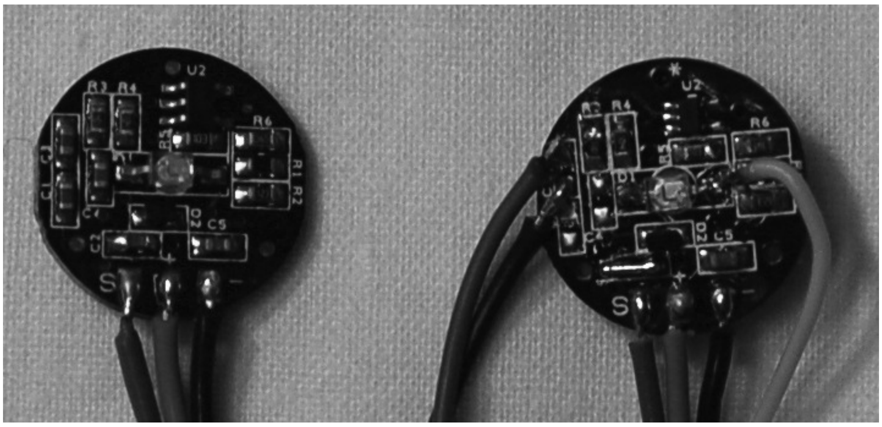


Figure 4-9: Modified Pulse Sensor Amped (right) compared to original. The two extra wires on the left carry the signal out to the analogue filtering components on the analogue board and back, and the wire on the right is connected through a replacement current limiting resistor on the analogue board to the analogue common allowing the LED brightness to be varied.

4.1.6 Physical considerations

Black fabric was wrapped around the wrist over the sensor to exclude ambient light since this was a source of noise, particularly fluorescent lamps which flicker at 100 Hz. The protective case for the sensor analogue and digital boards had to be light and comfortable against the skin whilst protecting the circuit boards and wiring. The solution adopted was to fold U-shaped troughs from thin thermoplastic, held together using nylon bolts, and sewed onto the fabric as shown in Figure 4-5.

The printed circuit board containing the isolators and Arduino was originally intended to go over the hand, so that the USB and power cables would extend from the finger tips. However, the board twisted the sensor when the wearer moved which lifted the sensor away from the skin. The design was changed so that the long board extended up the arm, and a second fabric strap closed with Velcro held the sensor assembly firm.

4.1.7 Data recording program

The data recording program was modified as a result of experience at the start of data collection. The display of the pulse waveform on the laptop was updated at 20 Hz, but this did not provide a good representation of the actual data because only one point was plotted every 50 ms to limit computational load and the datum plotted would often be affected by noise. This frequently gave a misleading impression of the signal amplitude. The data collection program was modified to display the data after a low pass filter had been applied to it (although the data was still stored unfiltered). A signal quality indicator was also added which updated every two seconds which verified that the amplitude of the filtered signal was between sensible limits although it did not prove very effective.

4.2 Method

Approval was obtained from the University Health and Psychology Departmental ethics committees (see Section D.2). The participants had five minutes of pulse data recorded at the left wrist in each of a range of sitting, standing and supine poses and with different left arm positions. In the sitting pose the participant had their feet flat on the floor, legs uncrossed and their right arm on the desk. They were permitted to read magazines, and so there was some head movement and right arm movement, but the participants were encouraged to move as little as possible and to avoid speaking.

Care was taken to ensure that standing poses mimicked the sitting poses as closely as possible – a box was placed on the desk to raise the effective height of the flat surface by 65 cm and the participant placed their right arm on the box. The supine poses similarly mimicked the left arm positions of the sitting and standing poses. The individual poses were taken in a fixed order, except where repeated at the end of the run because of exceptional noise or other problems.

4.2.1 LED brightness adjustments

Some pulsatile signals measured by the sensor had very low amplitude, and the resulting poor signal to noise ratio adversely affected the results. Consequently, the device was modified between participants 11 and 12 to allow the LED brightness to be optimised before the start of the run to maximise the signal amplitude.

This was carried out by removing the surface mount LED current limiting resistor R1 (see Figure 4-7) and running a wire from the pad which had connected it to the LED, to a header pin on the analogue board. An adjacent header pin was connected to the analogue common so that different resistors could be connected across the two headers. Figure 4-9 shows a modified Pulse Sensor Amped board.

The optimum pulse signal was obtained by working through a selection of different resistor values whilst monitoring the pulse waveform amplitude using the data recording program's graphical display. It was anticipated that the greatest signal amplitude would be achieved by setting the LED to the maximum intensity which did not saturate the photosensor. However, a counter-intuitive nonlinear relationship between the LED brightness and the signal amplitude was seen, in which substantially reducing the LED brightness could increase the pulse signal amplitude. It took several participants before this was fully understood, and the reason identified as non-linearity in the APDS-9008 photosensor. The effects of this were examined in detail, motivated in part by a concern that this non-linearity could affect the measured pulse waveform shape, and the results are presented in Section 4.10.

4.2.2 Offline processing

Data processing was based on the methods developed in the earlier work followed by classification of the pulse waveforms using a multilayer perceptron. However, there were a number of modifications which reflected both a better understanding of the processing requirements and the new hardware.

The time resolution was upgraded from milliseconds to microseconds to correspond to the new data format. This had some unforeseen consequences, such as where the previous code iterated through all millisecond values for some operations, it ran much more slowly iterating through all microsecond values instead since there were a thousand of these for every millisecond. This required the code to be rewritten to only step through microsecond values which were actually present. With the time resolution change the absolute maximum amount of jitter observed was only 11 μs.

The major processing stages were similar to the previous study, and are shown in Figure 4-10. There were some differences however, principally in the baseline correction and range of acceptable pulse rates.

Most pulse waveforms ended at a higher or lower value than they started because of the imperfect removal by high pass filters of the quasi-DC component. This was exacerbated by the hardware design of the new sensor because it raised the cut-off frequency of the analogue high pass filter to reduce the settling time following a large motion artefact. As in the previous study, the average gradient for each waveform was calculated from the start and end values and timestamps. However, whilst the earlier study discarded 7% of pulse waveforms by looking for a gradient exceeding 100 units per second, with the new sensor this corresponded to about 20% of the waveforms and the limit was removed. The baseline of the pulses was adjusted assuming that the underlying low frequency signal changed linearly, i.e. that the gradient was constant. Section 4.7 examines the effect of removing pulses with a steep gradient.

In addition a review of the plot of waveforms rejected showed that the original 600 ms to 1200 ms limits rejected genuine pulse waveforms and the limits were widened to 300 ms to 1500 ms and the software for splitting the timestamped datastream individual pulse waveforms modified accordingly.

The artefact removal stage used outlier removal, where waveforms with an attribute outside of 1.5 times the interquartile range away from either the upper or the lower quartile were removed. The attributes used were the minimal set of five used in the previous study (T_d, T_r, T_r/T_d, I_{nd}, I_r/I_d). The same attributes from the waveforms which survived the outlier removal step were used by a multilayer perceptron classifier implemented by Weka 3.6.12, in the same manner as described in Section 3.3.7.

4.2.3 Testing

Extensive checks were made to ensure the correct operation of the analysis programs. The `process()` method wrapping every step could be configured to produce plots of the input and output which could be visually checked. This was particularly useful after the data had been split into individual pulse waveforms for the second stage of processing. Every individual pulse waveform was assigned a unique identifying code and could be tracked though the system. Numerous sanity checks were included in the code which halted the program on failure. The

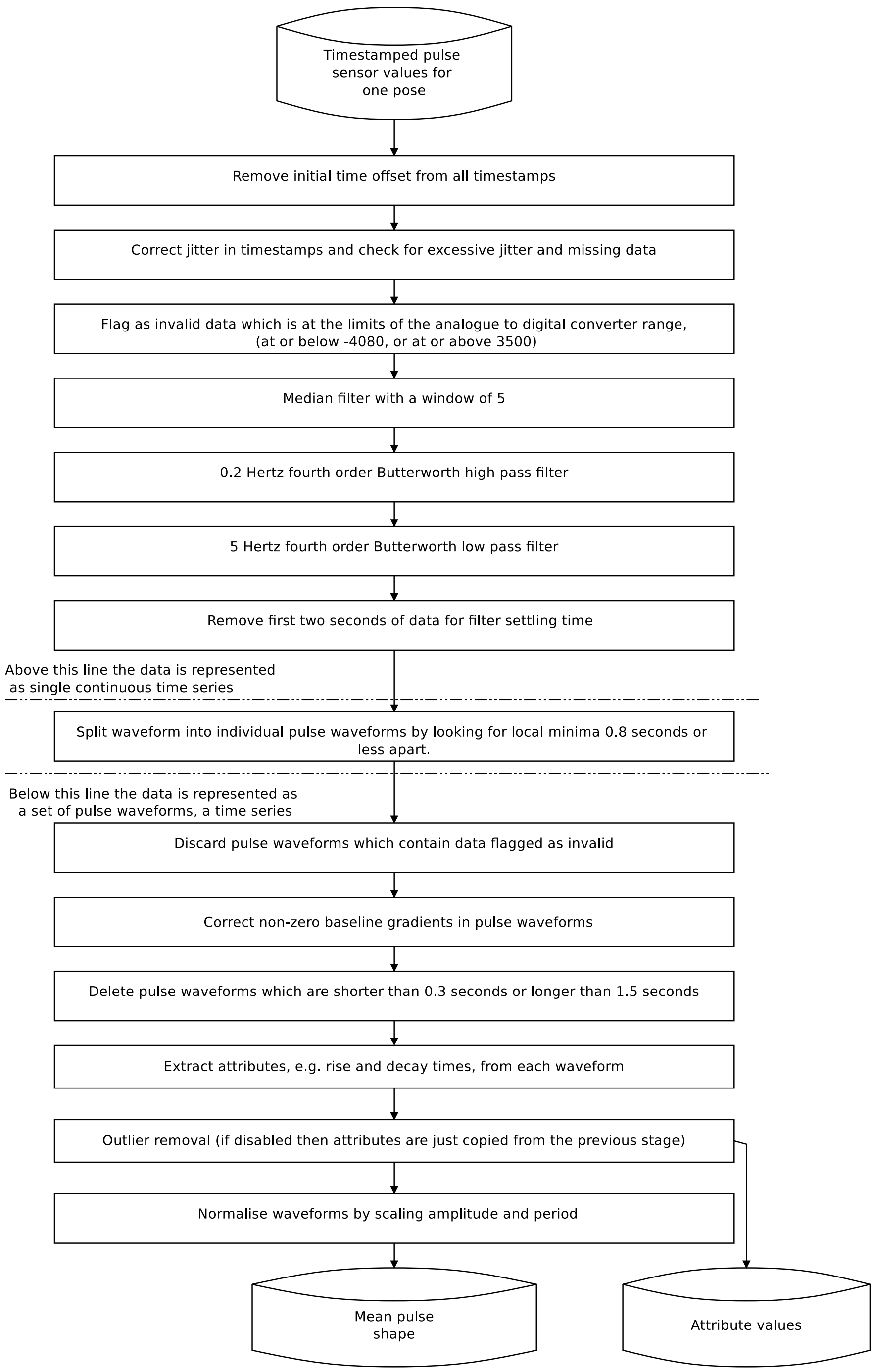


Figure 4-10: Principal processing steps for analysing pulse data collected, Section 4.2.2.

script for running the software had a regression mode which carried out a run using known input parameters and automatically compared the final output files with a prior saved set.

The processing was highly automated, for example the analysis runs were controlled by a script which used a control file specifying the filter settings, attributes, and other run settings. As well as the extensive output files, a directory containing a summary of each run was created. This contained a dozen key files containing a summary of the outputs, such as classifier results, pulse amplitudes, numbers of pulses extracted and classified.

A copy of each important summary directory was stored in the Subversion code management system, and any regenerated result routinely compared against this. In addition, one complete analysis run with fixed settings was run automatically at the end of the script execution and the results compared with a saved version of this directory for the same parameters and any changes reviewed.

4.3 Participants

The participants were healthy adults in age range 20–65 recruited through word of mouth. They were given £5 for taking part. Consent was taken in writing. The same exclusion criteria were adopted as in the previous study described in Section 3.3:

- Conditions which prevented the participant standing for more than ten minutes.
- Conditions which might grossly distort the pulse shape, for example missing a limb, having a pacemaker, very fast/slow heart rate or very high/low blood pressure. If the condition was controlled by drugs to bring it back into the normal range, then the participant was not excluded.
- Skin conditions which might contaminate the sensor or cause discomfort.
- Insufficient agility to lie on floor and get up again.
- Inability to give informed consent.

Five minutes of pulse waveform data were recorded from the top of the left arm about 3 cm from the wrist as in the earlier study. Table 4.2 shows the poses used, with the number of supine poses reduced and standing poses increased because of the small effect of arm position in the supine poses. The first three standing poses were matched to the sitting poses by having the arms in the same position so that as far as possible the only difference was that the participant was standing rather than sitting.

Number	Pose
0	Sitting at a desk with the left arm resting on the desk. Feet flat on floor. Right arm on desk.
1	Sitting at desk as above but with left arm hanging down.
2	Sitting at desk as above but with left arm across the chest roughly at the level of the heart. The participant could clutch their clothing with their left hand to help support their arm.
3	Sitting at desk as above but with left arm resting on left thigh.
4	Standing with left arm hanging by side.
5	Standing but with left arm across the chest roughly at the level of the heart. The participant could clutch their clothing with their left hand to help support their arm. Right arm bent 90 degrees at elbow and resting on a supporting box.
6	Standing with the arms bent 90 degrees at elbow and resting on a supporting box.
7	Supine on back with left and right arms straight and parallel to body.
8	Supine on back with left arm across the chest roughly at the level of the heart. The participant could clutch their clothing with their left hand to help support their arm. Right arm straight and parallel to body.
9	Supine on back with hands clasped on abdomen.

Table 4.2: Poses used in the study

4.4 Results

Eighteen participants were recruited in an age range 21–63 (median 34, 14 female), providing about 1.5 GB of raw data. Table 4.3 shows the results using ten-fold stratified cross validation with the multilayer perceptron for categorising poses into sitting, standing or lying down.

The goal of the study was originally to collect data from six participants in each decade of age between 20 and 65, but as it progressed an appreciation developed that the major difficulty was in accurately measuring pulse shape, which shifted the emphasis to improving the sensor and the signal processing.

Substantial variations in pulse signal amplitude were observed between poses, and even more so between participants. There were two orders of magnitude difference in median amplitude between some participants, and in those participants where the amplitude was small the signal was strongly affected by noise. Because of this the sensor was modified following participant 11 to allow the LED illumination intensity to be manually adjusted at the start of the run, as described in Section 4.2.1.

Participant	Sex	Age	Median pulse amplitude	Total pulses	Correctly classified	Success rate	Kappa κ	$\sigma_{r,p}$ of rise/decay time ratio
11	M	61	3434	2323	2175	94%	0.90	0.21
5	F	21	234	3469	2871	83%	0.74	0.24
12	F	63	2503	2522	2081	83%	0.73	0.20
1	F	56	273	2994	2385	80%	0.69	0.16
18	M	32	366	3079	2246	73%	0.58	0.25
2	F	28	157	2789	1978	71%	0.56	0.31
9	F	34	238	3535	2392	68%	0.51	0.39
15	M	54	423	3402	2267	67%	0.49	0.23
3	F	25	195	2693	1795	67%	0.49	0.35
7	F	33	86	3278	1931	59%	0.37	0.40
16	M	34	109	3389	1935	57%	0.36	0.50
14	F	23	91	2924	1665	57%	0.35	0.43
8	F	31	117	3070	1665	54%	0.30	0.43
4	F	29	114	2852	1539	54%	0.30	0.41
17	F	27	261	2756	1453	53%	0.26	0.49
13	F	46	341	3051	1576	52%	0.25	0.24
10	F	60	27	3926	1949	50%	0.19	0.60
6	F	61	34	3598	1609	45%	0.13	0.60
median		34	215	3061	1942	63%	0.43	0.37
mean		40	500	3092	1973	65%	0.46	0.36
sd		15	919	412	371	14%	0.21	0.14

Table 4.3: Results using the same digital filter settings as first study. Ordered by descending Kappa values for multilayer perceptron classifier results following window size 5 median filter, 0.2 Hz 4^{th} order Butterworth high pass filter, 5 Hz 4^{th} order Butterworth low pass filter, with five attributes and outlier removal.

4.5 Analysis

The performance of the classifier was much worse than in the previous study with Cohen's Kappa κ values corresponding to substantial agreement or better for only 22% of the participants.

The results, Table 4.3 also shows a large variation in pulse signal amplitude, covering two orders of magnitude, despite the same brightness LED being used for the first 11 participants. There is a clear correlation between larger amplitudes and higher κ. Kappa is affected by both the quality of the pulse waveform data and by the participant's physiological responses. Different participants may show more or less differences between pulse waveform attributes with pose, and these differences will be blurred by noisy pulse shape measurements. A suitable data quality metric is needed to allow an assessment of the data quality which does not also include the classifier performance.

4.6 Data quality measure

The data quality from each participant can be assessed by examining the spread of attribute values for each pose. There will inevitably be some random variation due to physiological effects but the spread will also be affected by noise and artefacts in the measurement. Whilst this can be done by looking at Kappa, that also factors in the classifier efficiency. The ratio of rise time to decay time of the pressure peak (T_r/T_d in Table 3.5) is a sensitive measure because it is affected by noise interfering both with the pressure peak rise and decay time measurements. In addition, as a combination of two measurements it will suffer more dispersion than either of them individually. A relative standard deviation of this attribute was calculated for each participant pose dataset:

$$\sigma_r = \frac{\sigma}{\mu} \tag{4.1}$$

where μ is the mean of the pulse pressure peak rise time/decay time ratio T_r/T_d and σ its standard deviation. The pooled relative standard deviation for each participant dataset is produced using the formula:

$$\sigma_{r,p} = \sqrt{\frac{\sum_{i=0}^{9}(N_i-1)(\frac{\sigma_i}{\mu_i})^2}{\sum_{i=0}^{9}(N_i-1)}} \tag{4.2}$$

where i is the pose number in Table 4.2 and N is the number of pulse waveforms in the pose, and thus the number of pulse pressure peak rise time/decay time ratio observations in it. A single pooled metric for entire study dataset can be produced by iterating i through each participant and pose. This differs from taking the mean of the $\sigma_{r,p}$ values for each participant because it weights each waveform equally instead of each participant.

There was a good correlation between higher Kappa values and smaller $\sigma_{r,p}$, as plotted in Figure 4-11, suggesting that reducing $\sigma_{r,p}$ would improve κ.

4.6.1 Outlier removal performance

Outlier removal improves the results, as can be seen by comparing Table 4.4, the results with outlier removal disabled with Table 4.3, the results with outlier removal enabled. It reduces $\sigma_{r,p}$ of the rise/decay time ratio by a median of 43%, at a median cost of 13% of the pulse wave-

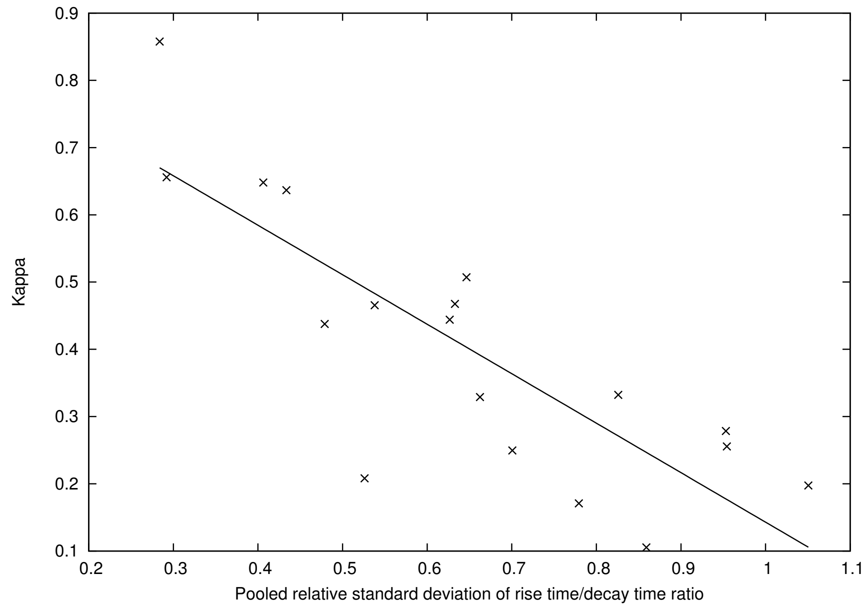


Figure 4-11: Smaller variation in attribute measurements in each pose improves the classifier performance. This figure shows classifier performance represented by Cohen's Kappa for each participant versus the pooled relative standard deviation of T_r/T_d, the ratio of pressure peak rise time to decay time $\sigma_{r,p}$, with a least squares fit. These results are for outlier removal disabled, so that the full spread of the T_r/T_d attribute is shown.

forms. This improves the classifier performance, probably mainly by removing waveforms which are randomly classified, with Kappa increasing by a median of 0.05.

4.6.2 Pulse signal amplitude

The LED light scattered back by the skin to the photosensor is largely constant, with the pulse modulated variation accounting for around 1% of the total. The small amplitude of the pulse signal makes it vulnerable to the effects of noise, and some noise is within the same frequency range as the pulse signal, particularly motion artefacts which either cause tissue movement or changes in the optical coupling between the sensor and the skin.

There was a positive correlation between small values of the data quality metric $\sigma_{r,p}$, signifying better quality data, and the pulse amplitude, as shown in Figure 4-12. This was true regardless of whether outlier removal was enabled or not, although the effect of enabling it was to markedly reduce $\sigma_{r,p}$ simply because it removed the values with the largest deviations.

This supports the suggestion that small pulse amplitude signals suffered more from noise than larger ones, and reflects the difficulty in measuring pulse shape at the wrist where the density of capillaries is relatively poor and informed the decision to modify the hardware to

Participant	Median pulse amplitude	Total pulses	Correctly classified	Success rate	Kappa κ	$\sigma_{r,p}$ of rise/decay time ratio
11	3301	2538	2316	91%	0.86	0.28
12	2458	2825	2188	77%	0.66	0.29
5	231	3971	3065	77%	0.65	0.41
1	273	3364	2557	76%	0.64	0.43
18	351	3677	2490	68%	0.51	0.65
2	151	3282	2144	65%	0.47	0.63
9	235	3920	2530	65%	0.47	0.54
3	189	3146	1994	63%	0.44	0.63
15	413	3718	2346	63%	0.44	0.48
16	105	4021	2231	55%	0.33	0.83
7	83	3771	2121	56%	0.33	0.66
14	86	3467	1818	52%	0.28	0.95
4	107	3362	1724	51%	0.26	0.95
8	114	3545	1795	51%	0.25	0.70
13	334	3463	1678	48%	0.21	0.53
17	236	3313	1611	49%	0.20	1.1
10	26	4360	2007	46%	0.17	0.78
6	33	4079	1732	42%	0.11	0.86
median	210	3506	2133	60%	0.38	0.64
mean	485	3546	2130	61%	0.40	0.65
sd	890	453	382	13%	0.20	0.23

Table 4.4: Results using same digital filter settings as the previous study, but with outlier removal disabled. Ordered by Kappa values for multilayer perceptron classifier results following window 5 median filter, 0.2 Hz 4^{th} order Butterworth high pass filter, 5 Hz 4^{th} order Butterworth low pass filter, with five attributes.

allow the illuminating LED brightness to be adjusted, as described in Section 4.2.1.

The pulse shape measurements did not produce uniform pulse amplitudes for each participant/pose combination, but a range of amplitudes. If the small amplitude pulses are discarded and the larger retained, then these will have a larger signal to noise ratio.

Table 4.5 shows how rejecting small amplitude waveforms affects the results. Removing small amplitude pulses reduces the relative standard deviation of the remaining ones. The effect is less pronounced for the very large pulses, from Participants 11 and 12, which presumably are less affected by noise.

The conclusions drawn from this are to reinforce the importance of obtaining the largest possible amplitude pulse signals, and that small amplitude pulse signals should be discarded as too vulnerable to noise and artefacts.

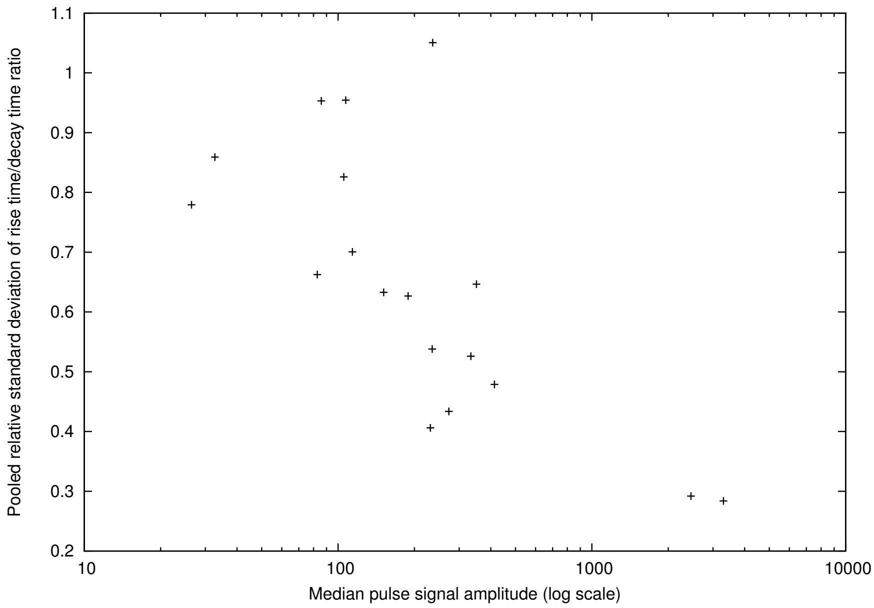


Figure 4-12: Higher amplitude pulse pressure peak signal amplitudes reduce the dispersion of measured values of the ratio of pressure peak rise time to decay time $\sigma_{r,p}$. Even ignoring the effect of the two participants who produced very large amplitude pulse signals (bottom right), the benefit of larger pulse signal amplitudes in reducing $\sigma_{r,p}$ is clear since most of the participants who had pulse signals above a median amplitude of 200 had $\sigma_{r,p}$ values below 0.7. Outlier removal disabled.

4.7 Baseline correction

The possible effect of large baseline corrections was a concern because of the assumption that the low frequency signal had a constant gradient over the length of the pulse waveform. It was more important in this study because the analogue high pass filter cut-off frequency was higher than in the previous study to reduce filter settling time, and let more low frequency signal through. The effect on $\sigma_{r,p}$ for the rise time/decay time ratio of changing the maximum acceptable gradient is shown in Figure 4-14.

Any waveform which has a greater mean gradient than the maximum acceptable one is discarded, those with less have their baselines adjusted assuming that the baseline gradient is constant, as shown in Figure 4-13. $\sigma_{r,p}$ rises approximately linearly until the gradient reaches about 100 units per second, and thereafter any further increase only adds about 1% to $\sigma_{r,p}$. Hence providing a gradient limit above 100 units per second has little effect and the limit was removed.

Participant	Median pulse amplitude	$\sigma_{r,p}$ of pressure peak rise/decay time ratio						
		Threshold (units)						
		None	50	100	150	200	250	300
11	3301	0.28	0.28	0.27	0.27	0.27	0.27	0.27
12	2458	0.29	0.29	0.29	0.29	0.28	0.28	0.28
5	231	0.41	0.36	0.35	0.33	0.31	0.32	
1	273	0.43	0.28	0.25	0.25	0.27	0.28	
15	413	0.48	0.47	0.43	0.34	0.26	0.24	0.22
13	334	0.53	0.47	0.46	0.41	0.34	0.28	0.26
9	235	0.54	0.49	0.48	0.46	0.44	0.37	0.31
3	189	0.63	0.44	0.43	0.42			
2	151	0.63	0.44	0.40	0.36			
18	351	0.65	0.60	0.57	0.55	0.54	0.52	0.51
7	83	0.66	0.51					
8	114	0.70	0.54	0.45				
10	26	0.78						
16	105	0.83	0.68	0.64				
6	33	0.86						
14	86	0.95	0.62					
4	107	0.95	0.68	0.48				
17	236	1.1	0.99	0.94	0.83	0.73	0.59	
median	210	0.64	0.48	0.44	0.36	0.31	0.28	0.27
mean	485	0.65	0.51	0.46	0.41	0.38	0.35	0.31
sd	890	0.23	0.18	0.18	0.16	0.16	0.12	0.10
no. pulses		63822	52612	43721	34352	27774	22796	18971

Table 4.5: Effect of removing small amplitude pulses on the pooled relative standard deviation of T_r/T_d, the ratio of pressure peak rise time to decay time $\sigma_{r,p}$. Smaller numbers indicate less variation in measured values. Participant datasets containing less than 1500 pulse waveforms are not shown. 5 window median filter, 5 Hz low pass filter, 0.2 Hz high pass filter with no outlier removal. Ordered by $\sigma_{r,p}$ in the "None" threshold column.

4.7.1 Digital filter performance

The offline digital filtering, carried out before the data stream is broken into individual pulse waveforms, was a crucial noise removal step. The purpose of the analogue filter on the sensor board is to attenuate the quasi-DC component sufficiently to allow the AC component to be amplified without the residual quasi-DC component saturating the amplifier.

The digital filters further attenuated the residual low frequency signals and removed interference caused by 50 Hz mains and 100 Hz fluorescent lighting flicker. The effect of the digital filters is shown in Figure 4-15.

The effectiveness of the different filters was examined by selectively disabling them. As

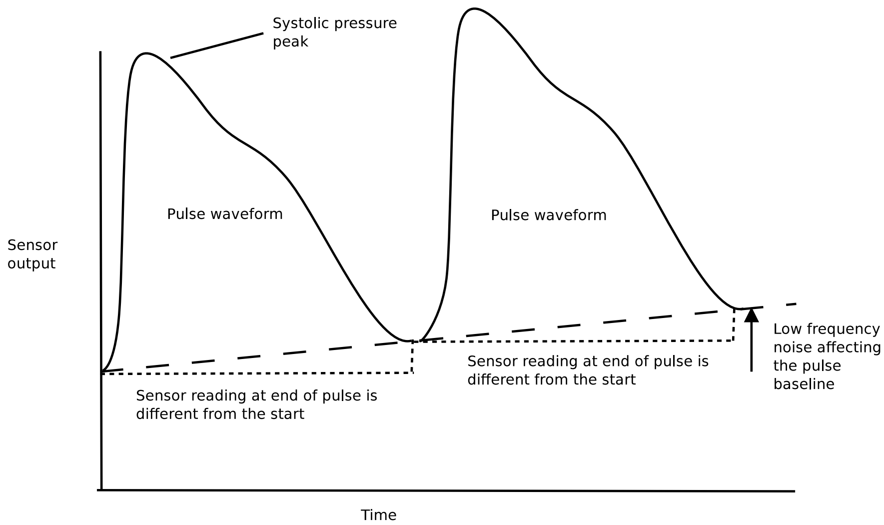


Figure 4-13: Most of the low frequency signal is removed by the high pass filters. The remnant affects the pulse signal baseline, so that the value at the end of a single pulse waveform is usually different to the start. Baseline correction compensates for this by assuming that it changes at a constant gradient over a pulse width.

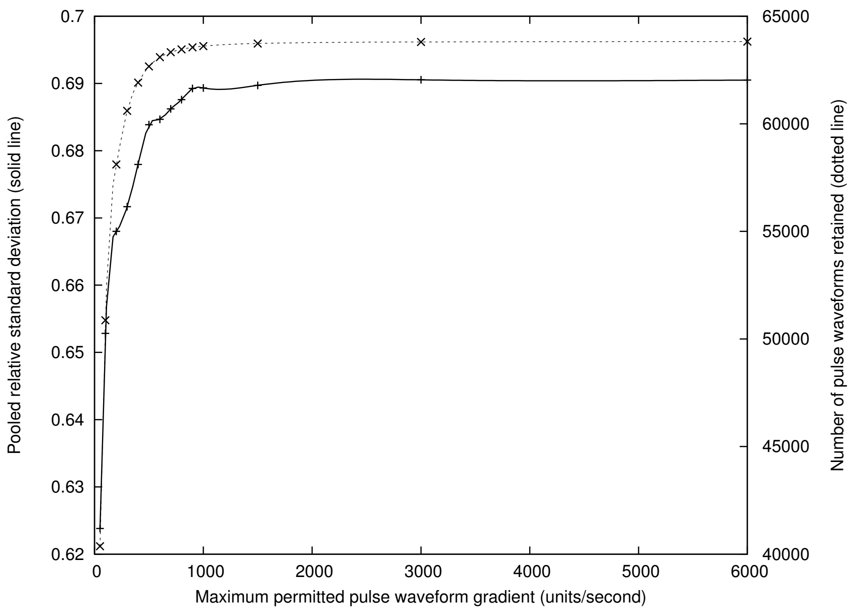
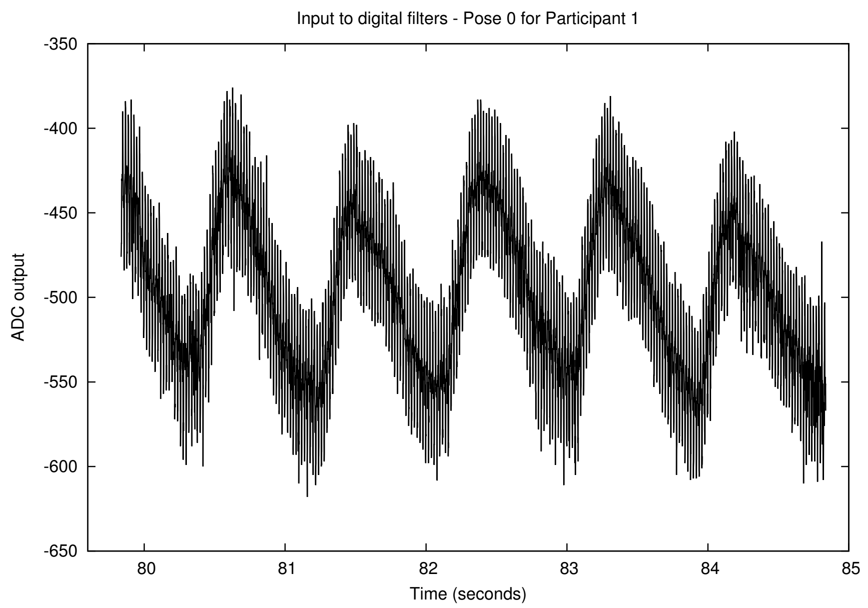
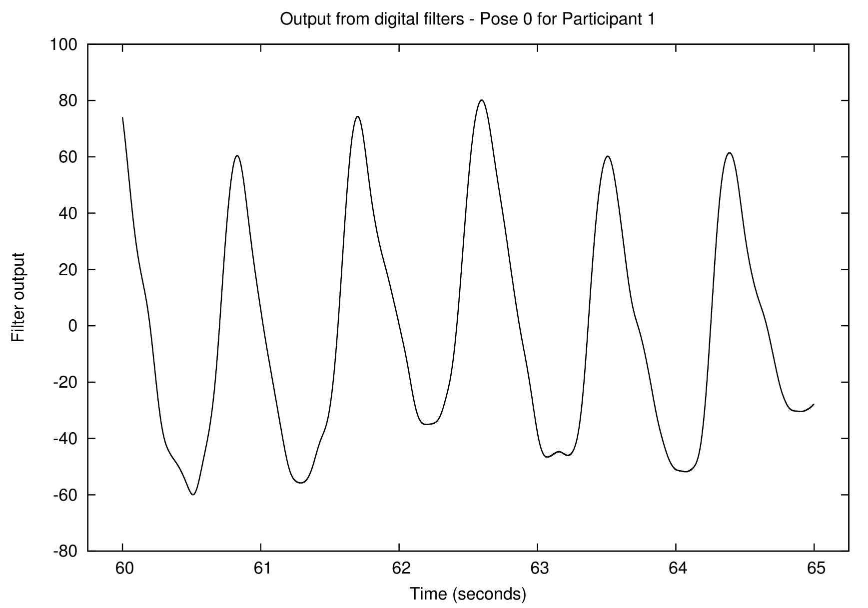


Figure 4-14: The effects of different maximum acceptable mean pulse waveform gradients. Waveforms are deleted where their mean gradient exceeds the value on the x axis. The curves show the effects on the $\sigma_{r,p}$ pooled relative standard deviation of the ratio of the rise time to decay time of the pressure peak (solid line), and the number of waveforms remaining after the maximum gradient (dotted line).



(a) Input



(b) Output

Figure 4-15: Comparison of the pulse signal before and after digital filtering using window 5 median filter, 0.2 Hz high pass, 5 Hz low pass Butterworth 4^{th} order filters. The data stream processing, described in more detail in Section 4.2.2, also removed the initial time offset from the data stream so the second plot shows the correct offset from the start of the run. This dataset was one of the those most affected by mains interference.

can be seen from Table 4.6, comparing columns A and C, the median filter had very little effect. This is hardly surprising as it acts as a low pass filter, and with a window size of 5 at 1500 samples per second it is operating at a frequency far above the low pass frequency filter.

Participant	A All filters HP+LP+Med	B No filters	C HP+LP	D HP+Med	E LP+Med
11	0.28	0.67	0.28	0.41	0.64
12	0.29	0.37	0.29	0.39	0.37
5	0.41	4.6	0.40	4.5	5.5
1	0.43	2.9	0.43	1.0	0.95
15	0.48	0.95	0.48	0.81	0.75
13	0.53	2.3	0.52	1.7	1.2
9	0.54	3.9	0.54	3.9	2.8
3	0.63	7.8	0.63	7.4	5.8
2	0.63	8.0	0.62	8.1	8.0
18	0.65	3.1	0.66	2.0	1.5
7	0.66	12	0.65	7.9	10
8	0.70	12	0.70	4.4	5.6
10	0.78	13	0.79	2.8	3.6
16	0.83	14	0.81	4.3	4.9
6	0.86	12	0.86	5.1	7.1
14	0.95	15	0.95	4.7	4.4
4	0.95	7.6	0.95	6.2	4.9
17	1.1	11	1.0	2.5	1.6
median	0.64	7.7	0.64	4.1	4.0
mean	0.65	7.3	0.64	3.8	3.9
sd	0.23	5.1	0.22	2.5	2.9

Table 4.6: The effect on the pooled relative standard deviation of the T_r/T_d (the ratio of the rise time and the decay time for each pulse), $\sigma_{r,p}$, of disabling the different digital filters. Baseline is column A, with window 5 median filter (Med), 0.2 Hz 4^{th} order Butterworth high pass filter (HP), 5 Hz 4^{th} order Butterworth low pass filter (LP), with five attributes. Ordered by $\sigma_{r,p}$ in column A.

Figure 4-16 shows the same input signal having been passed through a 30 Hz low pass filter to remove high frequency noise to make the underlying waveform discernible and the result after filtering. The filtered pressure peak width is narrower than the unfiltered signal, since the 0.2 Hz high pass filter suppresses gradual changes in the waveform.

Some other plots showed the minimum of the pulse waveform appearing much earlier than in the unfiltered curve, again because of the low pass filter cut-off. An example of this is shown in Figure 4-17, a sample from Participant 18 in a supine pose along with the output from the filters. However, the minima timing is not critical because the start of the rise, and the end

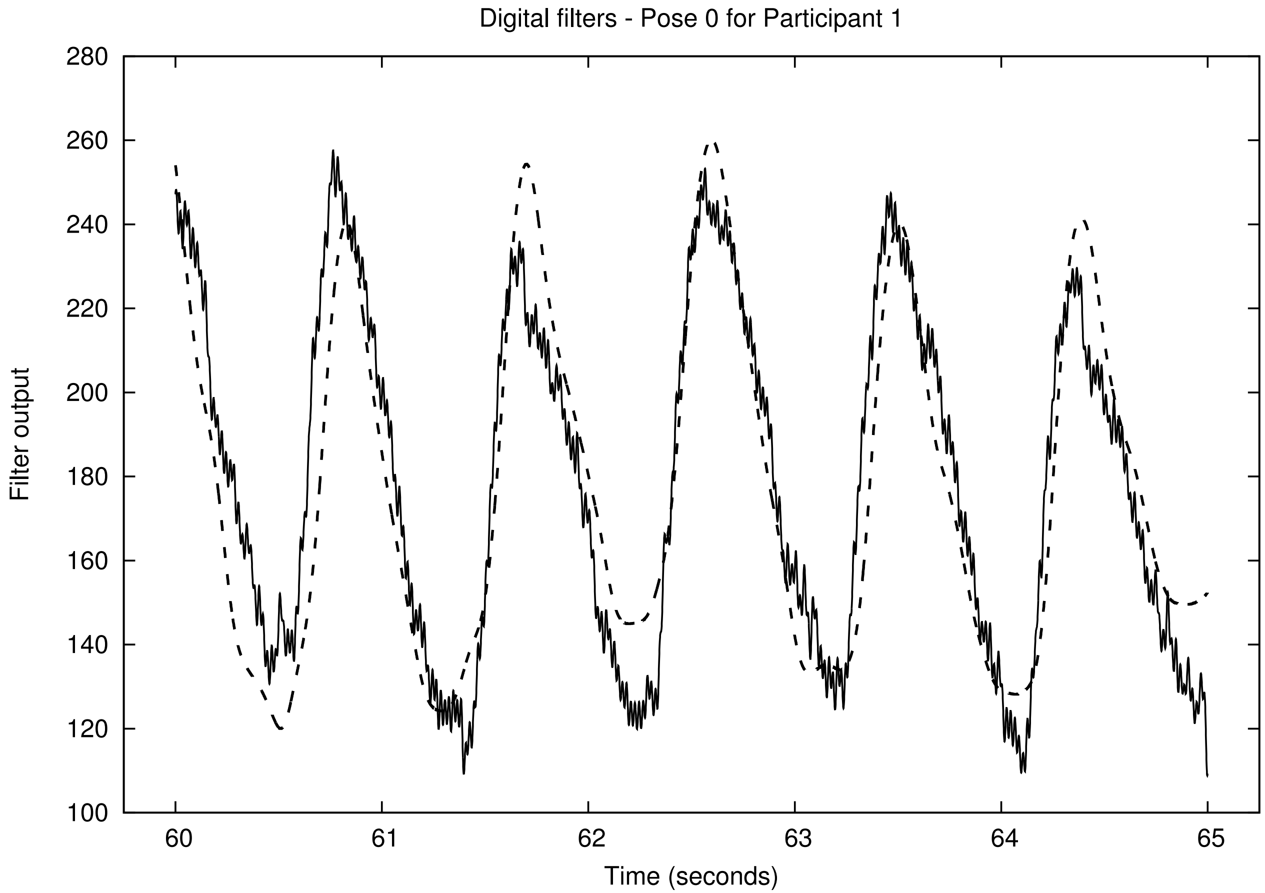


Figure 4-16: Comparison of underlying signal before and after digital filtering. The "unfiltered" signal (solid) has been passed through a 30 Hz low pass Butterworth 4^{th} order filter to remove the worst of the noise but minimise the shape distortion and the original can be seen in Figure 4-15. The filtered signal is the original passed through the window 5 median filter, 0.2 Hz high pass, 5 Hz low pass Butterworth 4^{th} order filters. This is a reasonable approximation to the unfiltered signal for the purposes of measuring pressure peak rise and decay timings.

of the decay, is taken at 15% of the amplitude rather than at the minimum point, although the distortion is sufficiently great in this plot that it is likely to have an effect.

Reducing the cut-off of the high pass filter to 0.1 Hz helps address the two distortions, as shown in the dotted line in Figure 4-17, but at the expense of much more interference from low frequency signals. The improvement in the rise time measurement is shown in Figure 4-18 which is a histogram of the decay times of the dataset using the two high pass filters. The lower frequency cut-off shows less variation in the rise times. However, the effect on attribute spread is more mixed across the datasets, as shown in Table 4.7.

Participant	$\sigma_{r,p}$	
	High pass filter cut-off	
	0.2 Hz	0.1 Hz
1	0.25	0.30
11	0.27	0.31
12	0.29	0.31
5	0.33	0.31
15	0.34	0.33
2	0.36	0.26
13	0.41	0.41
3	0.42	0.44
9	0.46	0.40
18	0.56	0.61
17	0.83	1.3
median	0.36	0.33
mean	0.41	0.45
sd	0.17	0.30

Table 4.7: Reducing the cut-off of the high pass filter to improve the accuracy of the waveform measurement has a mixed effect on the spread in measured attribute values. $\sigma_{r,p}$ is the pooled relative standard deviation of T_r/T_d, the ratio of pressure peak rise time to decay time $\sigma_{r,p}$. In both cases a low pass Butterworth 4^{th} order 5 Hz filter was also applied and a 150 unit amplitude cut-off, but no outlier removal. Participant datasets with less than 1500 pulses remaining after the 150 unit cut are not shown. Ordered by values for 0.2 Hz filter.

4.8 Final results

Whilst the median filter was unnecessary, the other two digital filters were effective. 0.2 Hz cut-off is less than ideal but represents a compromise between signal distortion and the introduction of noise. A much more sophisticated approach is really needed than a fixed cut-off frequency, but the filter is adequate for evaluating the viability of pulse shape measurements.

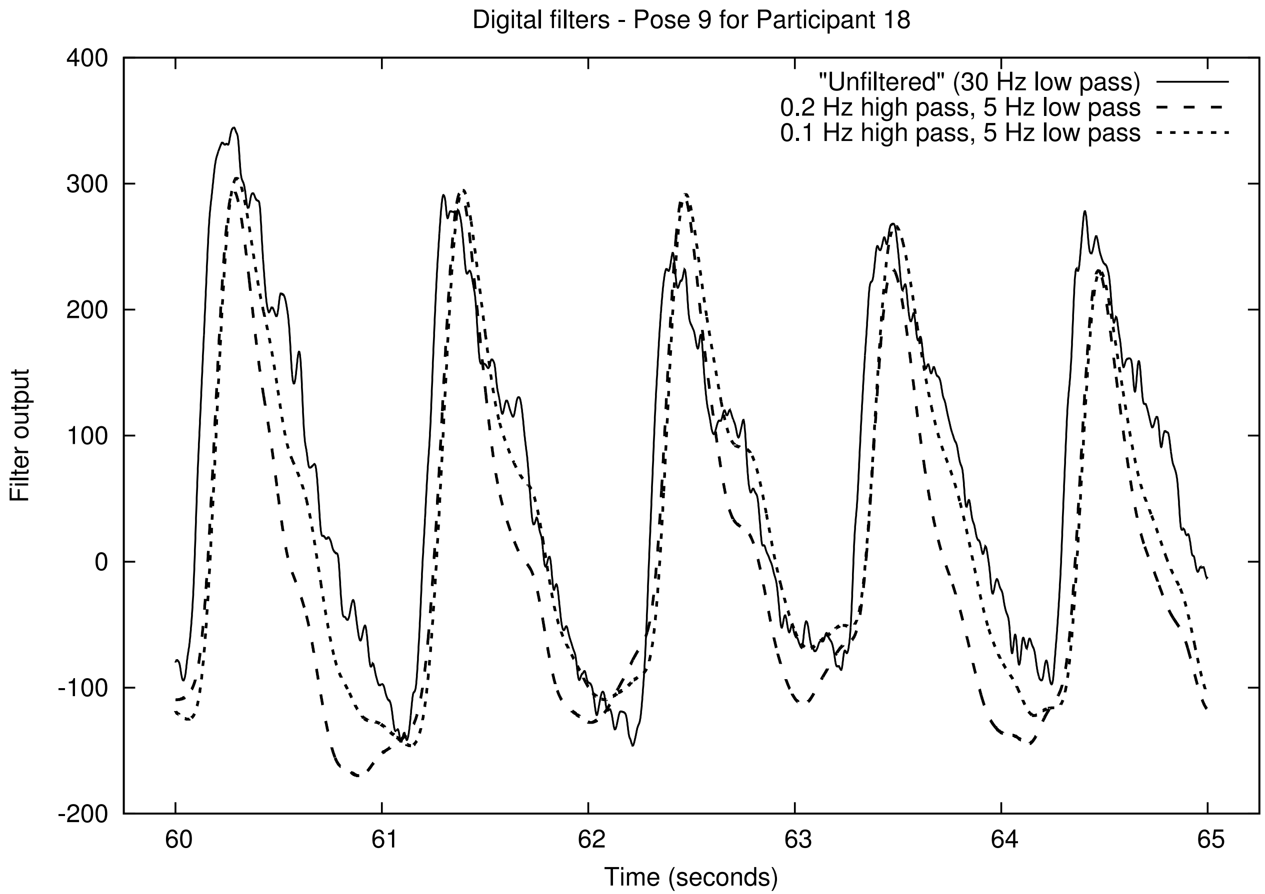
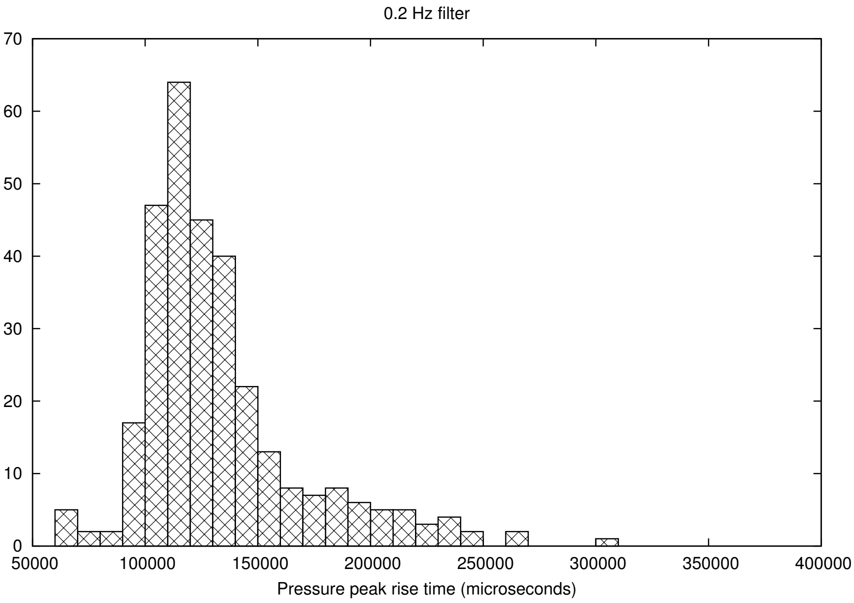
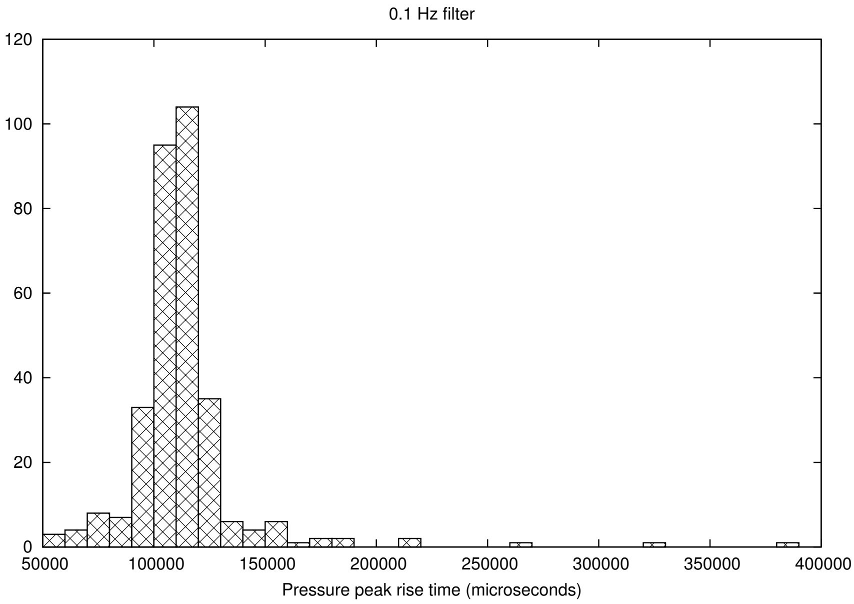


Figure 4-17: The effect of reducing the high pass digital filter cut-off frequency. The solid line shows the unfiltered pulse waveform (on the plot only, high frequency noise has been removed using a 30 Hz low pass Butterworth 4^{th} order filter). The dashed line is the waveform after passing through the 0.2 Hz high pass, 5 Hz low pass Butterworth 4^{th} order filters. The timings of the pressure peak minima are inaccurate and the peaks too narrow. The precise timings of the minima are not critical since the processing software uses 15% amplitude instead, but this is insufficient to overcome the problem. Reducing the high pass filter cut-off to 0.1 Hz reduces the distortion substantially (dotted line).



(a) 0.2 Hz high pass digital filter



(b) 0.1 Hz high pass digital filter

Figure 4-18: Reducing the cut-off of the high pass filter improved the accuracy of the waveform measurement by allowing the rise time to be measured more accurately. This shows the rise times for Participant 18, supine on back with left arm across chest. Upper curve is high pass Butterworth 4^{th} order 0.2 Hz filter and lower is 0.1 Hz. The lower plot has less variation. Low pass Butterworth 4^{th} order 5 Hz filter also applied, but no median filter and no outlier removal.

Small amplitude pulse signals were affected by noise far more than larger ones, and a minimum acceptable amplitude was needed below which waveforms would be rejected. Outlier removal is effective and should be retained. The results using a 0.1 Hz high pass and 5 Hz low pass digital filters with any pulse less than amplitude 150 being discarded are shown in Table 4.8.

Participant	Median pulse amplitude	Total pulses	Correctly classified	Success rate	Kappa κ	$\sigma_{r,p}$ of rise/decay time ratio
11	3315	2171	1999	92%	0.87	0.11
12	2459	2455	2028	83%	0.73	0.13
5	237	3258	2575	79%	0.68	0.18
3	199	1952	1490	76%	0.64	0.20
1	294	2698	2046	76%	0.64	0.11
9	305	2707	2064	76%	0.63	0.35
15	438	3206	2302	72%	0.57	0.21
18	377	2855	2047	72%	0.56	0.22
13	353	2939	1605	55%	0.31	0.22
17	313	1709	847	50%	0.19	0.41
median	333	2703	2037	76%	0.63	0.21
mean	829	2595	1900	73%	0.58	0.24
sd	1105	519	480	13%	0.20	0.11

Table 4.8: The elimination of low amplitude data improves the results considerably. Results for the multilayer perceptron classifier running with five attributes, using 5 Hz low pass filter, 0.1 Hz high pass filter, no median filter, and 150 unit amplitude removal enabled. Excludes datasets having less than 1500 pulses since the classifier requires a reasonable sample to prevent overfitting. Outlier removal enabled for the 5 features used. Ordered by descending κ. Compare with Table 4.3.

4.9 Discussion

The pulse shape variation with pose was measured in 18 participants. The results confirmed that the determining pose from pulse waveform was viable but that good signal amplitude was essential to ensure a good signal to noise ratio.

Whilst outlier rejection has a small effect, this specific technique is impractical in a real fall detector because it relies upon knowing the pose in advance. However, some simple scheme for identifying obviously distorted pulses would be beneficial since the inclusion of these in the datasets means that both the classifier's learning process and the waveforms presented for classification will be impaired.

The arm hanging down poses showed poorer results than the sitting or lying down ones, because of lower amplitude and more motion artefacts. The lower amplitude was probably because the blood return flow up the arm is opposed by gravity, and the motion artefacts are because small movements are magnified by the arm acting as a long unsupported cantilever.

Removing artefacts, noise and the quasi-DC component without distorting pulse waveforms is a challenge. Pulses which have similar amplitude to the noise can be discarded, in this case a cut of 150, which retains pulses that are much larger than twice the noise amplitude.

A better strategy for removing low frequency signals would provide benefits. The filtering was simple, and based on an existing inexpensive sensor with the minimum of modifications. However, the gentle roll off of the analogue high pass filter required a balance between its effect on the pulse waveform and its settling time and a higher order filter would have been beneficial. An improved design would also utilise a more unified approach to the design of the analogue and digital filters.

There is still a clear correlation between low amplitude datasets and low Kappa, with median pulse signal amplitudes only just above the cut-off point still giving poor results reinforcing the need for a high amplitude signal.

4.10 Photosensor response

The photosensor is used to measure the light scattered back from the skin, from which the very small AC component modulated by the pulse, shown in Figure 3-1, is extracted. The accuracy of shape measurements is dependent upon the linearity of the photosensor over the small light intensity range. Non-linearity will distort the pulse shape, for example if the sensitivity significantly reduces with intensity then the pulse shape will appear to be more flat-topped than it really is.

Photodiodes have a linear voltage response to light intensity in open circuit, but a logarithmic one in short circuit, and so the response will be somewhere in between in a practical circuit. Since the logarithm curve $ln(I)$ can be approximated by a linear relationship over a small range range δI, and with increasing fidelity as the range of decreases, the linearity of the sensor will increase as the variation in light intensity decreases.

Figure 4-20 shows the median pulse amplitude collected over two minutes with different LED current limiting resistors, and after 0.2 Hz high pass, 5 Hz low pass 4^{th} order Butterworth digital smoothing filters have been applied to the signal. The AC component voltage at the photosensor will be $1/130$ of the voltage seen at the ADC. However, it shows a strongly non-linear relationship between resistance and the pulse signal amplitude, which suggested that the photosensor response should be examined in more detail.

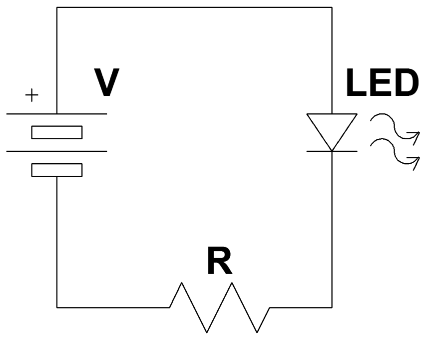


Figure 4-19: Basic LED circuit described by Equation 4.3.

The light intensity of an LED is proportional to the current through it. For the pulse sensor LED circuit consisting of a resistance R in series with a forward biased LED and a voltage source V, as shown in Figure 4-19, then:

$$Intensity \propto \frac{V - V_F}{R} \tag{4.3}$$

Where V_F is the LED's forward voltage, a characteristic of the device usually considered constant although in practice increasing slightly with current.

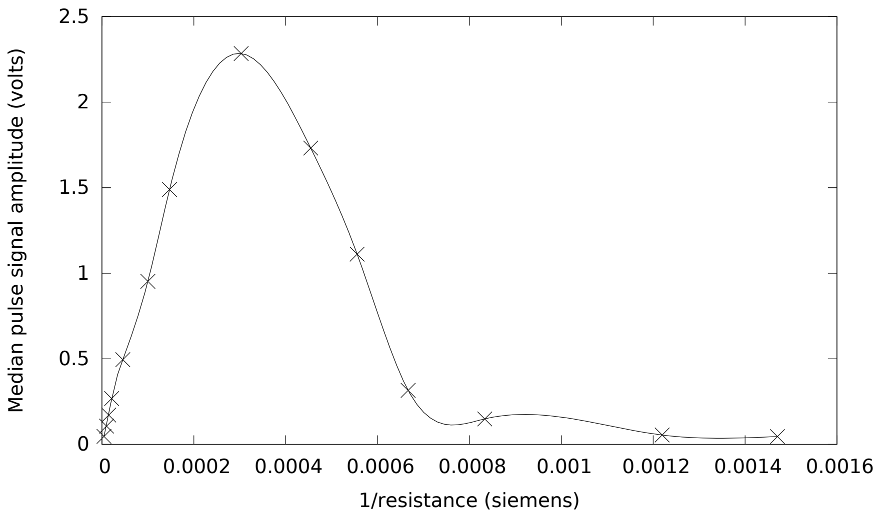


Figure 4-20: The brightest LED did not provide the largest amplitude pulse signal. The x axis, $1/R$, is proportional to the LED light intensity, and the y axis shows the median pulse signal amplitude measured on the laptop for a single participant. Points joined with a natural cubic spline.

The pulse sensor illuminates the skin and measures the intensity of the light reflected or scattered back to the device. This signal contains a large slowly varying DC component and a much smaller more rapidly varying AC component which is modulated by the blood flow.

The sensor uses a low pass filter to attenuate the DC component so that the AC component voltage can be amplified by approximately 130 without the amplifier being saturated by the much larger DC component which is at several volts. The ratio of the amplitudes of the original AC and DC components is called the component ratio.

The hardware low pass filter makes a precise estimate of the component ratio hard to produce, however the LED needed to be about ten times brighter for the wrist than the fingertip to produce a signal of similar amplitude. The maximum value seen for the component ratio has been reported as between 0.7% and 5.7% using imaging of the entire underside of the hand and wrist techniques (Kamshilin et al., 2015), and by Vizbara (2013) as about 3.5% using an LED and photosensor although it is not clear which part of the wrist was used. Maeda et al. (2011) reported component ratios of around 0.56% (sd 0.13%) and 0.62% (sd 0.14%) at room temperature for fingertip pulses.

The pressure applied by the sensor strap has an important effect, since Kamshilin et al. (2015) found the PPG signal amplitude using green light increased markedly as pressure was applied. Experiments with one participant showed the modulation depth increasing from 1% to 4% with increasing force up to about 0.5 N/cm^2, which the authors noted was substantially more than found by other authors (Rafolt and Gallasch, 2004) who used infrared light.

The APDS-9008 photosensor used in the pulse sensor is an analogue device based on a photoconductive mode photodiode. Ideal photodiodes have a linear short circuit current response to incident light intensity but a logarithmic open circuit voltage. Neither is likely in a practical circuit and the manufacturer's datasheet provided a graph of spot values representing the illumination/voltage relationship for different load resistances (Avago Technologies, 2008, Figure 10). The data was provided for a supply voltage of 1.8 V, but the response curves can be scaled for other voltages since the effect on their shape will be small as the only consequence of changing voltage in a photodiode is on the dark current. The pulse sensor supplied 4.63 V to the photosensor, 5 V less the 0.37 V forward voltage drop of diode D2, a Bourns CD0603-B00340 (Bourns, 2009). The manufacturer's data was also for a photosensor tested with white light, but the results are assumed to be applicable for the LED's green light.

A polynomial function was fitted using least squares to the spot values for the 12 kΩ load resistance used in the pulse sensor. An 8th order polynomial was used since its interpolated values deviated from the spot values by less than 1% (maximum 0.52%). From the curve, Figure 4-21, the brightest illumination will not give the largest amplitude AC component, since although there is a positive correlation between photosensor voltage and illuminance the photosensor sensitivity is reduced at higher brightnesses.

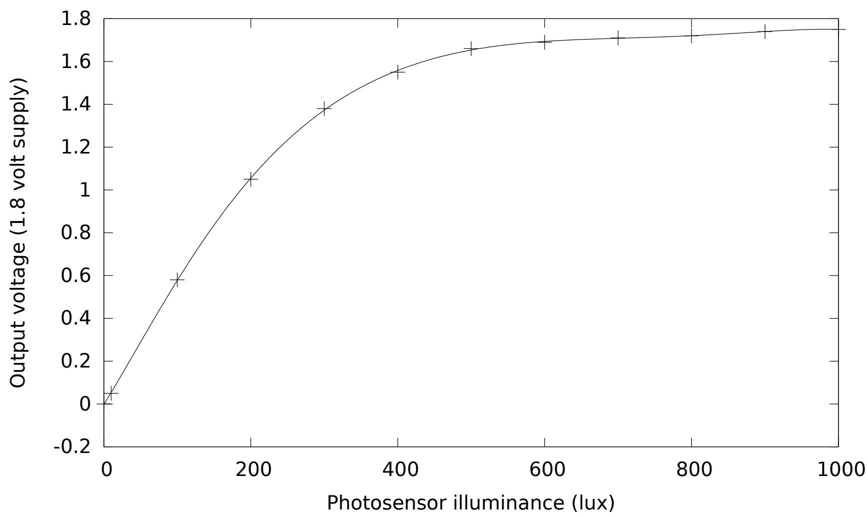


Figure 4-21: Manufacturer's values for APDS-9008 response with 12 kΩ load resistor, and fitted polynomial curve (Avago Technologies, 2008). The ideal light intensity for pulse measurements using this photosensor is 200 lx to 300 lx because this will provide the largest amplitude pulse signal (Figure 4-23) with a good linearity (Figure 4-24).

Consider what happens if the LED brightness is doubled. The illuminance at the photosensor will also double and hence the AC component, representing the pulse signal, will double but so will the fixed quasi-DC component signal. The doubled quasi-DC component will mean that although the photosensor will be responding to greater intensity illumination, and so greater variations, its sensitivity to those changes is reduced.

Hence the decreased sensitivity can more than compensate for the increased illuminance. The non-linear relationship between illuminance and photosensor response also means that the response will not be perfectly linear even over the small range of the AC component variation.

Two numerical analyses were run on the fitted polynomial, one to examine the sensitivity to small fractional changes in illuminance representing an AC component at the photosensor and the second examining to determine the maximum likely measurement errors due to photosensor non-linearity.

The sensitivity analysis iterated through DC component values in small steps and calculated the AC component amplitude for different component ratios. It then calculated the voltage variation corresponding to the AC component amplitude. The result is shown in Figure 4-23 and shows a good match with experiment, in Figure 4-20.

The second numerical analysis iterated through the range of quasi-DC components, and calculated the amplitude of the response to the AC component for different component ratios. It calculated the deviation of the response to the AC component from linear, as shown in Figure 4-

22.

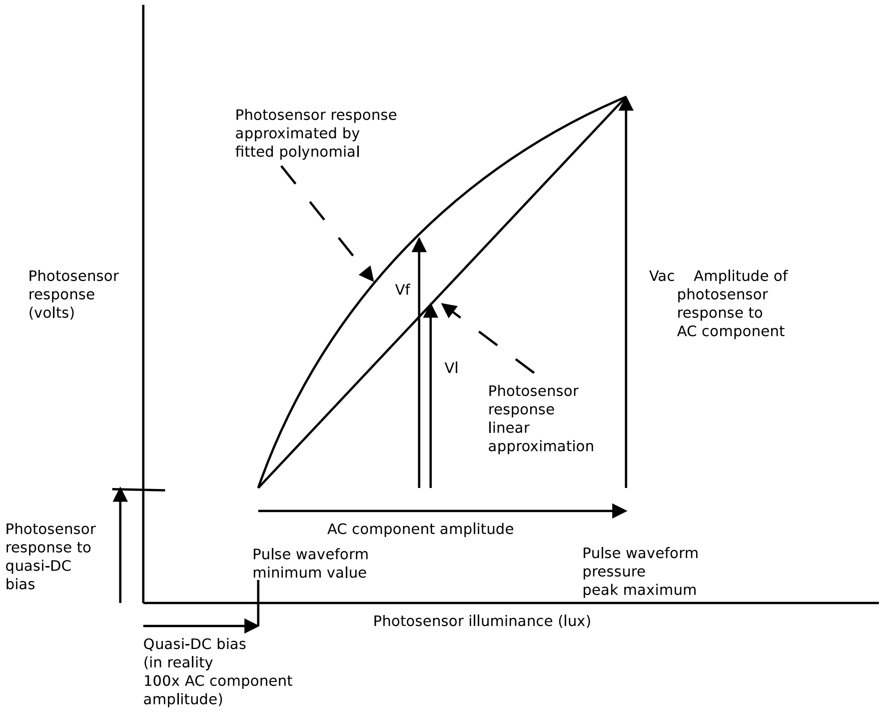


Figure 4-22: Determination the maximum measurement error due to photosensor response non-linearity. The pulse signal is a small intensity fluctuation above the much larger quasi-DC component. The response using the polynomial curve, which is close to the actual response, is V_f, whilst the linear approximation is V_l. The pulse sensor measures the pulse signal as values lying between 0 and a maximum amplitude V_{ac} corresponding to the AC component amplitude. The analysis determined the maximum value of $\frac{|V_f - V_l|}{V_{ac}}$. Using this, a value of 1% with a 10 mV AC component means the maximum error due to non-linearity will be 0.1 mV as a result.

The linear interpolation used the fitted curve voltages for the quasi-DC component light level and the quasi-DC component level plus the AC component amplitude as its baseline values. The results, Figure 4-24, show that the linearity even at 3% is well under 1% at 200 lx to 300 lx.

The 470 Ω LED current limiting resistor provided with the Pulse Sensor Amped was used for the first 11 participants in the second study. This gave a photosensor output voltage of 4.56 V when measured using the device on the wrist of a light skinned Caucasian. Scaling this to the manufacturer's 1.8 V photosensor response curve, Figure 4-21, gives an illuminance of about 490 lx. At this illuminance the AC component sensitivity is about half that at 200 lx, and hence reducing the LED brightness by increasing the current limiting resistor value will improve the signal amplitude.

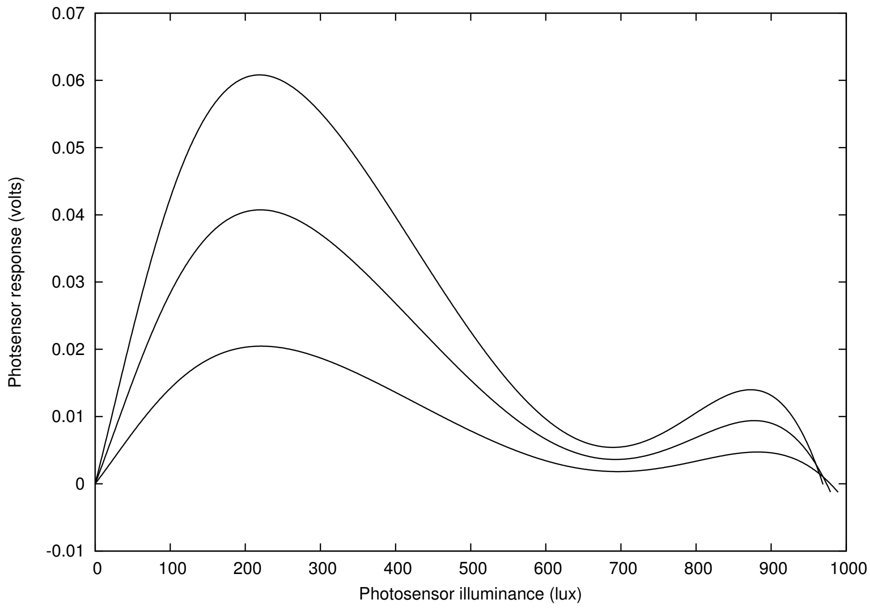


Figure 4-23: Results of modelling the photosensor sensitivity to small changes in light intensity using the response shown in Figure 4-21, and scaled to a 4.63 V photosensor supply. The ratio between the amplitude of the pulsatile signal and the much larger quasi-DC component is called the component ratio, and is about 1%. The three curves show the voltage changes seen for component ratios of 1% (bottom), 2% (middle) and 3% (top). The curves were generated using a polynomial fitted to the manufacturer's spot values for the APDS-9008 with a 12 kΩ load. The largest response to the small optical pulse signal modulation occurs at 200 lx to 300 lx.

4.10.1 Conclusion

The photosensor sensitivity curves, Figure 4-23, explain why the AC component amplitude is not proportional to the LED brightness. The optimum photosensor illumination intensity is 200 lx to 300 lx where the photosensor's sensitivity to the AC component is maximised and the linearity is good. Even for an exceptionally strong pulse signal, 3%, the non-linearity is better than 0.5%.

The photosensor response curve must be considered in a practical fall detector incorporating pulse shape. The response curves for photoconductive mode photodiodes are similar since the shape is governed by physics. Very low load resistances will produce more linear responses but also much lower amplitude signals, adversely affecting signal to noise ratio, whilst high load resistances provide larger signals but a logarithmic response. However, between these extremes the device can use this to its benefit by adjusting the LED intensity since the linearity is excellent where the sensitivity is at its maximum.

If the LED intensity is adjusted to place AC component in the optimum sensitivity region

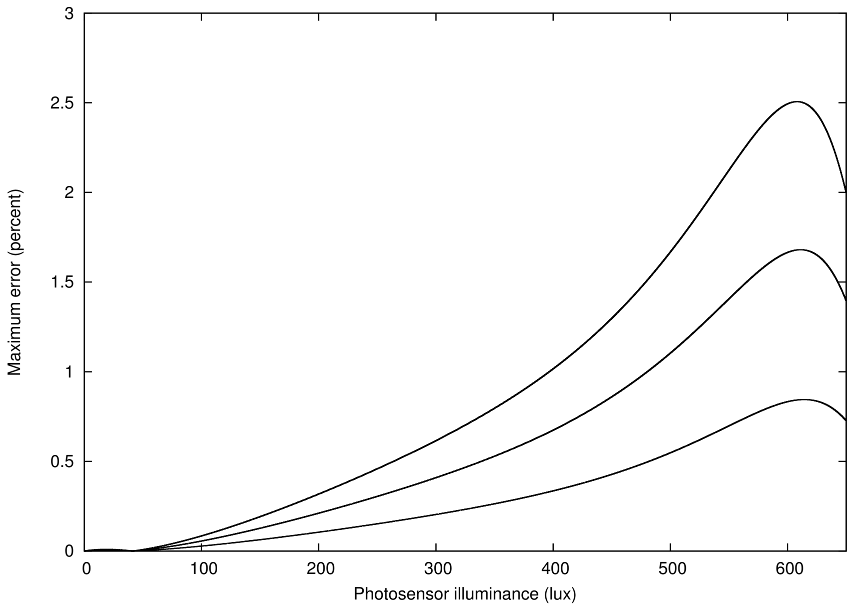


Figure 4-24: Results of modelling the maximum pulse signal measurement error due to photosensor non-linearity. The three curves show the voltage changes seen for ac component ratios of 1% (bottom), 2% (middle) and 3% (top). A component ratio of 1% is typical. This represents the small scale linearity of the photosensor response, Figure 4-21. The measurement error is good in the 200 lx to 300 lx region where the photosensor sensitivity to the pulse signal is optimal. The curves are generated using the polynomial fitted to the spot values for the APDS-9008 with a 12 kΩ load resistor, and so assume the photosensor is powered at 1.8 V.

then this is doubly beneficial because it both maximises the pulse signal amplitude, and thus the precision of the measurement, and operates the sensor in a region where linearity errors are very small.

4.11 Further sensor improvements

Whilst increasing the signal amplitude by changing the LED intensity offered the best prospect for improving sensor performance, other improvements can be made to reduce the magnitude of motion artefacts, and to improve the rejection of low frequency signals and other noise.

4.11.1 Mechanics

The sensor was still very sensitive to motion and so was lightened by removing the plastic fairing and the Pulse Sensor Amped board moved to a separate wrist strap to mechanically decouple it from any movement of the other circuit boards, as shown in Figure 4-25. The

Pulse Sensor Amped board itself was replaced as a solder pad was damaged during the reconstruction. A repeat of the tests on Participant 17 showed an improvement in $\sigma_{r,p}$, although with such a small sample other factors during the retest may have been more important. However, the modifications provided definite benefits by making the sensor physically much more manageable.

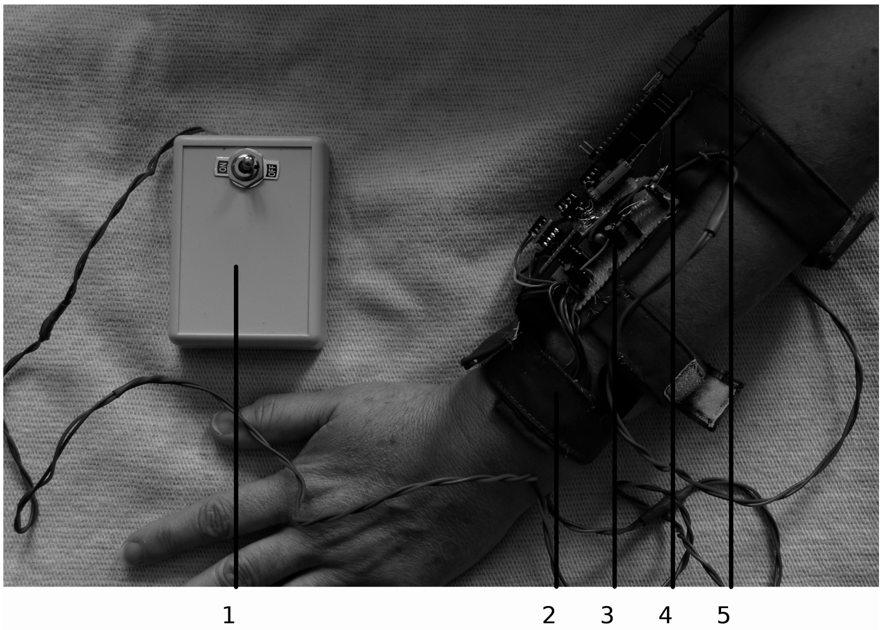


Figure 4-25: Improved green light pulse sensor following modifications. These were to permit LED brightness adjustment, and to improve the mechanics by removing the plastic fairing and moving the Pulse Sensor Amped to a separate wrist strap.

1. Battery box
2. Modified Pulse Sensor Amped
3. Analogue board
4. Digital board
5. USB cable to laptop

4.11.2 Analogue high pass filter

The analogue high pass filter removes the large quasi-DC component to leave the much smaller AC component which can then be amplified without saturating the amplifier. The filter cut-off was set as high as possible to reduce the lengthy settling time associated with motion artefacts seen in the previous study. However, the shallow roll off led to concerns that the relatively gentle decay of the pressure peak would appear shortened because its lower frequencies were removed as the high pass filter cut into the AC component frequencies. After some experimentation, the 3 dB cut-off was reduced to 0.3 Hz by increasing C3 to 22 µF.

4.11.3 Discussion

The mechanical modifications may have had an effect by lightening the sensor and the analogue filter change had a small effect on the waveform. An analogue filter with a sharper cut-off would have been beneficial as there was a compromise between removing too little quasi-DC component and distorting the signal. Whilst this could have been done in a new sensor design, the physical limitations of the existing hardware made it impractical.

However, the key to improving signal quality is really in increasing the signal amplitude. Experience of the system led to improvements, particularly in understanding of how illumination level affected the pulse signal amplitude, although this was not complete until well into the study. In particular the modelling of the photosensor led to an understanding of how reducing LED brightness, instead of increasing it, could improve the signal amplitude.

The next section examines using longer optical wavelengths to access thicker blood vessels where the changes in blood flow are greater.

4.12 Red light

The studies described so far used green light, but there are theoretical benefits to longer wavelengths because they penetrate further into the skin, where larger diameter blood vessels are present which would be expected to have a lower flow resistance. Murray et al. (2004) found that laser Doppler measurements of blood flow speed in a finger showed greater changes following occlusion and release by a cuff when red light was used than with green light. Transmission PPG universally uses infrared or red light because of the greater penetration.

The key metric is the *penetration depth* δ_p, the depth at which intensity falls to $1/e$ (37%) and sometimes expressed as its reciprocal, the *absorption coefficient*. However, the optical coefficients of skin are very difficult to measure and a review by Lister (2012) found an order of magnitude differences between some estimates. Whilst there is disagreement about specific values, there is agreement that longer wavelengths penetrate further into the skin, at least into near infrared.

Maeda et al. (2008) found that the scattering and reflection by skin tissue introduced more noise using infrared at 880 nm than using green light, particularly at temperatures below 15°C because the reduced perfusion in the upper dermal layers reduces the amplitude of the PPG signal. Other papers confirm this, for example Lee et al. (2013) recommended against using red (or blue) light in reflection PPG because of motion artefacts, and Maeda et al. (2011) repeated the recommendation of green over infrared because the smaller amount of scattering produces less noise. Both oxyhaemoglobin and haemoglobin absorb green light much more strongly than infrared, giving the AC component a greater modulation depth and thus improving the signal to noise ratio (Tamura et al., 2014). These observations have been confirmed by other researchers using white light sources and RGB cameras rather than monochrome light (Matsumura et al., 2014; Sun, 2011; Verkruysse et al., 2008), and the photoplethysmographic pulse rate sensors on the fitness bands and smart watches which have entered the marketplace over the last two or three years invariably use green light.

Nevertheless, the prospect of more freely flowing blood at depth made a brief evaluation of a longer wavelength worthwhile. A pulse sensor of the type described in Section 4.1.3, before the modification of capacitor C3 from 4.7 μF and without the plastic fairing, was constructed with the original Kingbright AM2520ZGC09 515 nm peak green LED replaced by an AM2520SURC09 645 nm peak red LED. Whilst the penetration depth of green light at 500 nm is 0.23 mm to 0.9 mm, for 600 nm it is 0.55 mm to 1.7 mm (Anderson and Parrish, 1981; Bashkatov et al., 2005).

Experiments with this sensor confirmed the findings from the literature, that whilst red light may be theoretically able to offer better performance than green, in practice the signal suffers far more from noise and artefacts. Figure 4-26 shows example pulse waveforms measured using the red sensor and the green one, and the conclusion was that using green light for the pulse shape sensor was preferable to longer wavelengths.

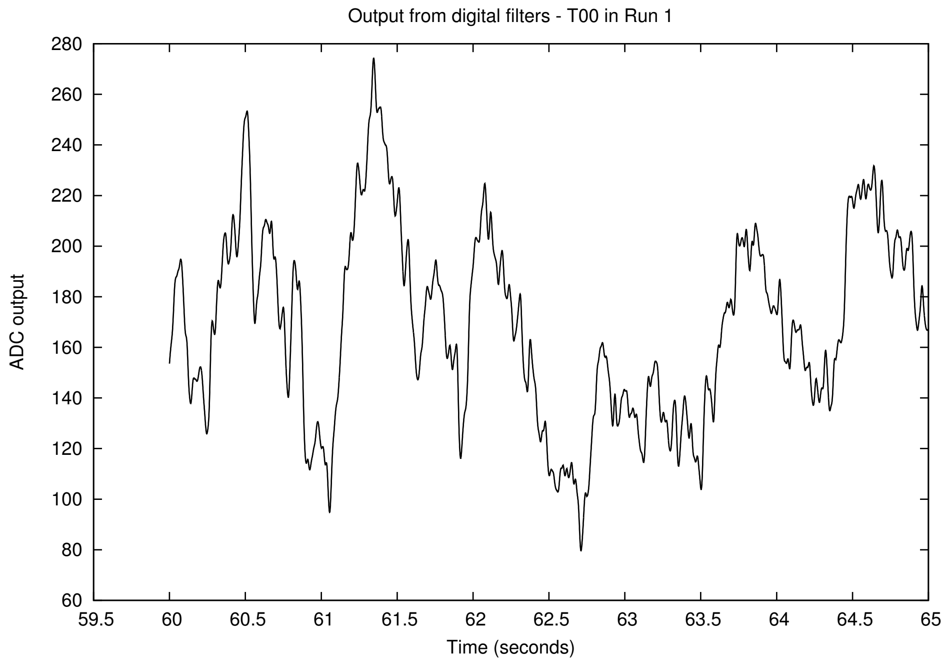
4.13 Limitations of the measurements

Despite the improvements, sensor noise remained a problem, which could be addressed by improved signal processing. A sharper high pass cut-off would have been preferable, and a low pass frequency cut-off meeting the Nyquist criteria desirable.

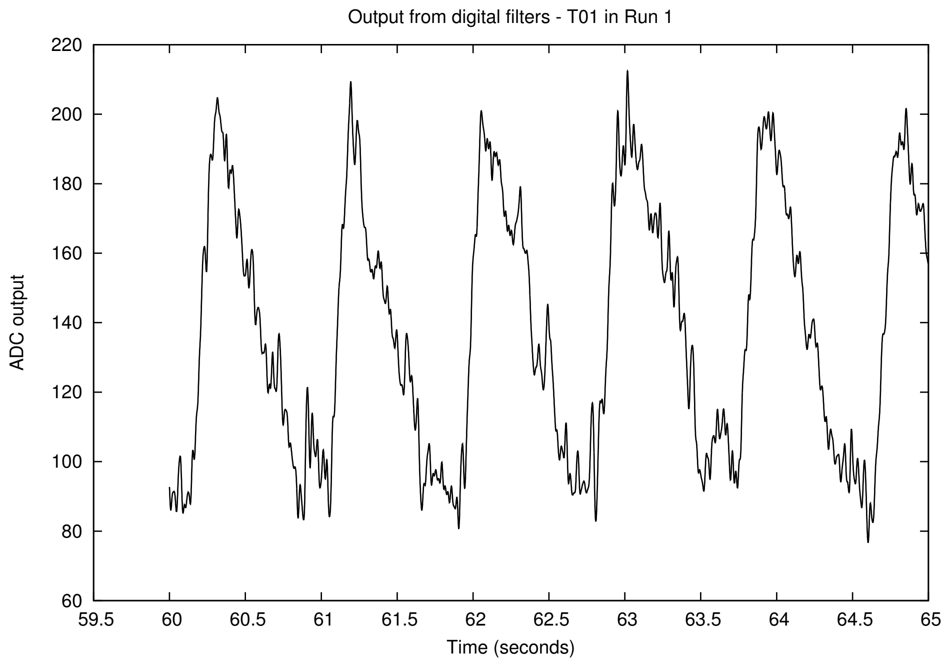
The study used a small sample of healthy volunteers, unrepresentative of the target population. Problems with the sensor meant that the technique was modified during the study to allow the LED brightness to be adjusted, and subsequently to make other modifications, although all measurements were made with essentially the same system.

Initially the motivation for adjusting the LED brightness was to be able to increase it to just below the sensor saturation point in the expectation that this would increase signal amplitude. This did not produce the anticipated result and it took experience with several participants before it was understood that the non-linearity of the photosensor meant that larger signal amplitudes were to be achieved by reducing, rather than increasing, LED brightness.

The steps to remove low frequency signals and other noise were pragmatic rather than systematic, and an improved sensor would employ more sophisticated data cleaning.



(a) Red 645 nm peak



(b) Green 515 nm peak

Figure 4-26: Examples of pulse waveform measured using red and green light at the wrist in the same pose, showing how red light produces a much poorer quality signal than green light. Data passed through 30 Hz low pass Butterworth 4^{th} order filter to remove high frequency noise.

The participants did not move the arm with the sensor attached and so motion artefacts were a relatively minor problem, but these will be an issue in a fall detector since the wearer will move around.

The attribute selection was pragmatic rather than methodical, since the priority was to evaluate the feasibility of the technique on a wider range of subjects and produce an improved sensor. Prioritising collecting the data allows a proper exploration of classifier attributes subsequently as time permits. This is a serious limitation since an understanding of how the classifier is using the different attributes is key to understand how it is operating.

The reliance on a few attributes is a weakness in the study. The study did not simulate the real conditions of a fall, and it is not known whether these characteristics are retained during periods of emotional stress.

4.14 Conclusion

This work confirmed that there is a useful relationship between pulse shape and body pose, but that measuring the pulse shape at the wrist is challenging. It is critical to obtain a large amplitude pulse to reduce the signal to noise ratio, for which an understanding of the photosensor characteristics is essential. Removing the quasi-DC component without affecting the pulse shape is a challenge.

The trial has not answered the question of whether the pulse shape could be used reliably if it could be measured with precision, but it is noteworthy that where there is a precise measurement the pose can be determined effectively. However, the work described in this chapter provides more confidence that the pulse shape could be a useful adjunct in fall detection alongside other information such as respiration and heart rate that a sensitive pulse sensor could provide.

The study did not use the target population for the fall detector, and an important next step is to examine the technique in a sample representing that group. This is particularly relevant because there are well-documented age-related changes to the pulse waveform, and the effects of dementia may also have an effect.

The understanding gained about how to improve signal quality in this study more than offset the initially disappointing results, and the substantial improvements in technique reaped dividends in the study on elderly people described in the next chapter.

Chapter 5

Body position from pulse shape in elderly people

The fall detector is intended for people with dementia, and it was important to corroborate the results obtained from young healthy people against older members of the population. Since elderly people make up the majority of people with dementia, they will exhibit the physiological effects of age combined with those of dementia.

There are difficulties in using people with dementia as experimental subjects, both around obtaining and maintaining informed consent and other problems that the condition brings (McKeown et al., 2010; Hubbard et al., 2003). The next section contains a brief literature review undertaken to determine whether elderly people without dementia would exhibit similar physiological responses to those with dementia in response to posture changes, and so be an acceptable alternative.

5.1 The physiological effects of changes in posture in older people and those with dementia

This section discusses the likely effects having dementia will have on pulse shape variation determined by photoplethysmography, compared to an age-matched group without dementia. It is sufficient to consider just Alzheimer's Disease (AD) and Vascular Dementia (VaD) as together they are responsible for almost all dementia.

Photoplethysmographic measurements reflect changes in blood flow in the tissue under examination (de Trafford and Lafferty, 1984). The cerebral microvasculature of people with AD shows numerous pathological differences compared to that of people of the same age without the disease (Buée et al., 1994; Farkas and Luiten, 2001; Hunter et al., 2012; Kalaria, 1996;

Zlokovic, 2005). These are so pronounced that the resulting reduction in cerebral perfusion has been hypothesised as the key mechanism for the neuron necrosis which is the major clinical symptom (de la Torre, 2002; Hunter et al., 2012). However, these major structural changes are not reflected in the peripheral vasculature.

Reduced cutaneous vasodilation has been observed in patients with AD and Dementia with Lewy Bodies (DLB) compared to age matched controls when measured using laser Doppler flowmetry on the middle third of the forearm in response to acetylcholine (Algotsson et al., 1995; Khalil et al., 2007). In practical terms this manifests itself as a smaller subcutaneous blood flow increase following exercise (Kálmán et al., 2002) and probably means that microvascular thermoregulatory responses are similarly impaired.

There is also abundant evidence of significantly reduced baroreflex response in AD, over and above the usual deterioration in baroreflex response with age, as well as in the neuropathalogically similar DLB and chromosomally related Parkinson's Disease (Goldstein, 2003; Oka et al., 2007; Szili-Török et al., 2001). In a study by Meel-van den Abeelen et al. (2013) the control group had a mean baroreflex response of $3.6\,\mathrm{ms\,mm^{-1}}$ Hg (sd $0.8\,\mathrm{ms\,mm^{-1}}$) in contrast to $1.6\,\mathrm{ms\,mm^{-1}}$ Hg (sd $1.3\,\mathrm{ms\,mm^{-1}}$) for the AD cohort. Significantly, the mild cognitive impairment group also had reduced baroreflex response, $2.3\,\mathrm{ms\,mm^{-1}}$ Hg (sd $1.4\,\mathrm{ms\,mm^{-1}}$), possibly because the insular cortex, the cerebral structure which mediates the baroreflex, suffers early compromise in AD (Royall et al., 2006). Laosiripisan et al. (2015) found impaired baroreflex response was correlated with reduced perfusion of the hippocampus, a structure damaged in the early stages of AD (Fox et al., 1996). Hence, baroreflex homeostasis in AD may be degraded both by deterioration in the central nervous system baroreflex mechanisms and simultaneously by a reduction in microvascular vasodilatory ability caused by reduced peripheral nervous system cholinergic response. These accompany deterioration of the same physiological systems which occur through ageing (Gupta and Lipsitz, 2007).

Reduced subcutaneous blood flow will attenuate the flow-modulated pulsatile waveform, mimicking the effects of lower temperatures (which also reduces flow (Rowell, 1977)). One of the reasons that green light is usually preferred over infrared for reflection photoplethysmography is its better performance at low skin temperatures (Maeda et al., 2008), and this may be of benefit here.

Impaired baroreflex will have a different effect. Changes in pulse shape with pose are probably mediated by gravity, both directly through blood flow hydrodynamics and indirectly through the baroreflex response (Linder et al., 2006; Leake et al., 2014). Hence, variations in baroreflex response are likely to affect the change of pulse shape with posture. The baroreflex operates by modifying cardiac output whilst sympathetic nervous activity constricts peripheral veins in response to increased pressure detected by the stretching of vessel wall smooth muscle. A compromised baroreflex results in higher blood pressure variability (Rodrigues et al., 2011), for example orthostatic hypotension is common in Alzheimer's (Mehrabian et al., 2010; Zakrzewska-Pniewska et al., 2012).

In the context of pulse shape change it is not immediately obvious whether the baroreflex would act to maintain a constant pulse shape by compensating for changes in blood pressure or provide a mechanism which actively drives pulse shape change. However, it is likely that pulse morphology will show greater differences with pose in an individual with AD than in one without since the less competent the baroreflex, the greater the likely effect of pose change on the peripheral microvasculature.

The same argument can be applied to the reduced venous vasoconstrictive responses, insofar as the constriction of blood vessels as a result of their engorgement is a feedback mechanism that maintains uniform blood flows. If this mechanism operates poorly when stressed by orthostatic changes, then greater differences are likely to be seen than if it performs well.

The second most common cause of dementia after AD is Vascular Dementia. The endothelial response to acetylcholine is reduced in people with pure Vascular Dementia (and vascular cognitive impairment) but to a much smaller degree than in Alzheimer's (Khalil et al., 2007). However, Vascular Dementia covers a spectrum of cerebrovascular conditions including multiple large infarcts, subcortical arteriosclerotic encephalopathy and small vessel ischemic disease (Craft, 2009; Kirshner, 2009) in contrast to the single distinctive neuropathy of AD. Some specific types of VaD produce unusually poor vasoconstrictor performance. For example, CADASIL shows significant selective systemic microvascular vasoconstrictor abnormalities (Gobron et al., 2007) and Binswanger's Disease produces increased peripheral vascular resistance (Iwamoto et al., 2003).

Orthostatic hypotension is common in people with Vascular Dementia (Allan et al., 2007; Mehrabian et al., 2010) which suggests that the baroreflex response is impaired. Hence, VaD will have the same effects as Alzheimer's Disease from the perspective of using photoplethysmography to determine pose, but probably to a lesser degree because of the association between the hippocampal and insular cortex damage of AD and baroreflex response impairment. In summary, AD and VaD have similar effects on baroreflex response and sympathetic vasoconstriction but VaD does so to a lesser degree. It is likely that the effects of these diseases would be to slightly attenuate the pulsatile signal at warm temperatures but make pose-related changes in photoplethysmography morphology more prominent.

Hence, elderly people are likely to be a satisfactory alternative in pulse shape studies to people with the most common two forms of dementia since the physiological effects which bring about pulse shape change with pose are likely to be greater in people with dementia.

5.2 Experimental study

A small study was carried out to determine if the pulse shape could be used to infer information about pose in elderly people. It was undertaken because age-related physiological changes may cause difficulties with wrist-based pulse waveform measurement due to the changes in waveform shape with age caused by the stiffening of arterial walls. In addition, the skin loses elasticity and bulk as people age, which may cause problems measuring the pulse shape. Therefore, a second, fingertip, sensor was used as a backup in case the wrist sensor data was too noisy. Whilst the target users of the fall detector are people with dementia, the literature review concluded that elderly people without dementia would be an acceptable alternative.

The planned study was for six healthy participants aged between 65 and 85, with the option to extend the number to 10 if poor pulse signals were obtained.

5.3 Apparatus

The wrist-worn pulse sensor developed in the previous study, including the changes described in Sections 4.11.1 and 4.11.2, was used alongside a similar device which monitored the pulse on the fingertip. The fingertip device had the same electronics as the wrist version but the physical layout designed for attachment to the back of a fingerless glove. The modified Pulse Sensor Amped board was fastened to the fingertip using surgical tape. Both sensors were worn on the left arm, as shown in Figure 5-1.

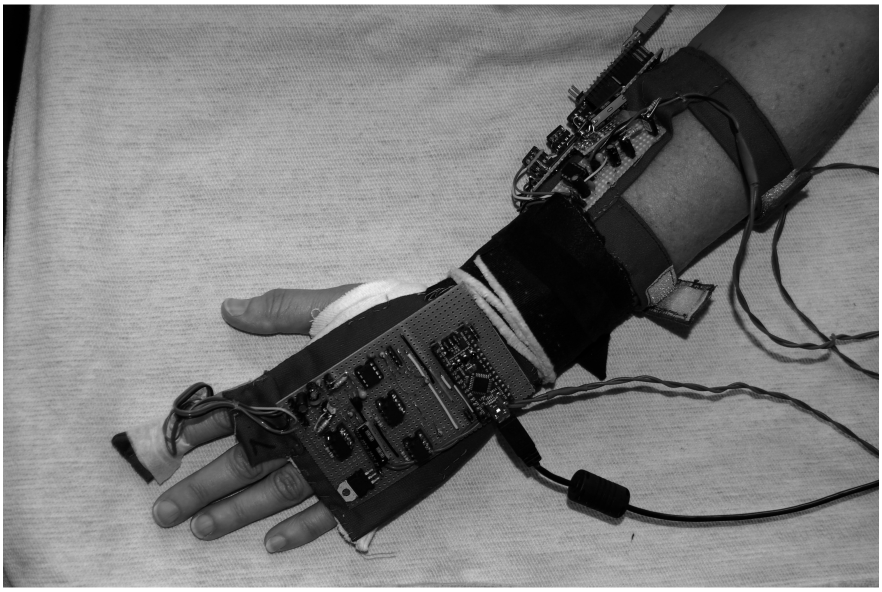


Figure 5-1: Elderly study wrist and fingertip sensors

The laptop data recording program was modified to simultaneously record data from two devices as shown in Figure 5-2. It was about 3,400 lines long and, as in the previous studies, followed a producer/consumer architecture with one thread, the producer, reading serial data and writing it to a concurrent queue, and a second thread, the consumer, transferring the data from the queue to a file.

Since the study used two sensors, one on the wrist and the other on the fingertip, the Arduino firmware in the fingertip sensor was modified so that it sent an ASCII “F” instead of a “P” at the start of each datum. This allowed the data recording program to discriminate between the two sensors. A single data file was written containing the data from both devices which was split during subsequent offline analysis. A synthesised example file is shown below:

Listing 5.1: Example start of data file

```
# VERSION: BlogTwin 1.0
# PARTICIPANT: 4
# POSE: Sitting at desk, left arm hanging down
# DATETIME: Thu, 25 Jun 2015 15:23:36 +0100
F 1807267200 -1475
F 1807267864 -1482
F 1807268532 -1478
F 1807269196 -1482
F 1807269868 -1480
F 1807270532 -1480
F 1807271196 -1486
P 1807175820 615
P 1807176484 611
P 1807177152 612
P 1807177820 610
```

5.4 Participants

The study was approved by the University Department for Health ethics committee, and the Psychology Committee chair indicated that Health approval alone was sufficient (see Section D.2). All participants were recruited through word of mouth and the measurements took place in their own homes or other agreed location.

Participants were excluded if they had medical conditions which might obviously affect the results – for example missing a limb, having a pacemaker, clinical bradycardia, tachycardia, hypotension or hypertension unless brought into the normal range by medication. They also needed sufficient agility to be able to stand from lying on a couch, and to stand comfortably for fifteen minutes.

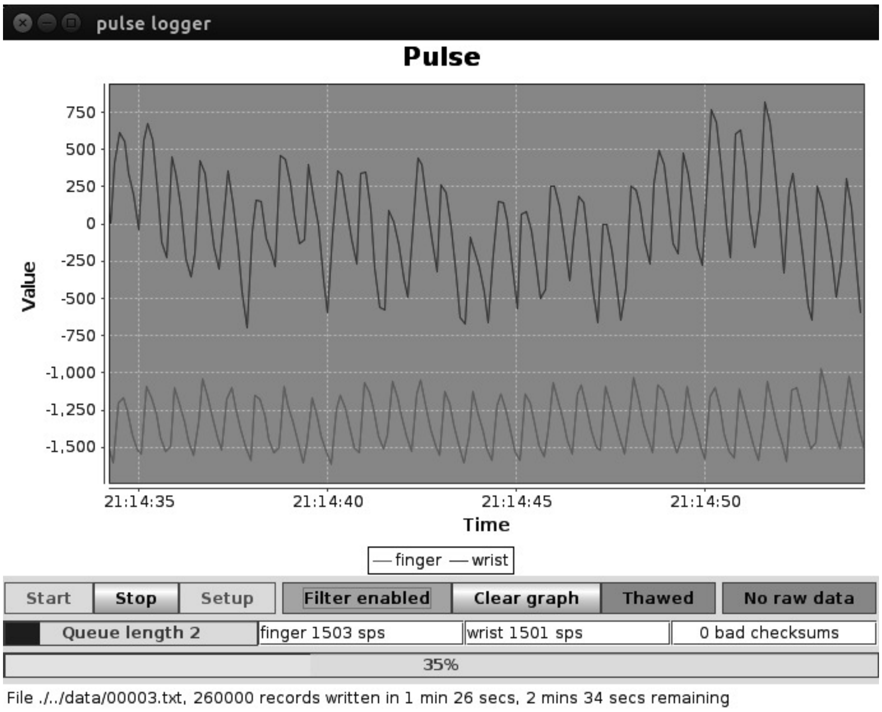


Figure 5-2: Data recording program display for study with dual wrist and fingertip sensors. The uppermost trace is from the fingertip sensor. Although it has a larger amplitude, the LED intensity used is about a tenth that of the wrist sensor.

Six participants were recruited, of whom half were female, with an age range of 74–84, (median 78).

5.5 Method

Pose	Description
0	Participant sitting with arms bent at elbow at 90 degrees and resting on a table or desk
1	Participant sitting with left arm dangling by side, right arm on table
2	Participant standing with arms bent at elbow at 90 degrees (and supported)
3	Participant standing with left arm dangling by side, right arm bent at elbow (and supported)
4	Participant lying on couch with arms by side
5	Participant lying on couch with hands over abdomen
6	Participant sitting with arm bent at elbow at 90 degrees (i.e. repeat of pose 0)

Table 5.1: Poses used in the study

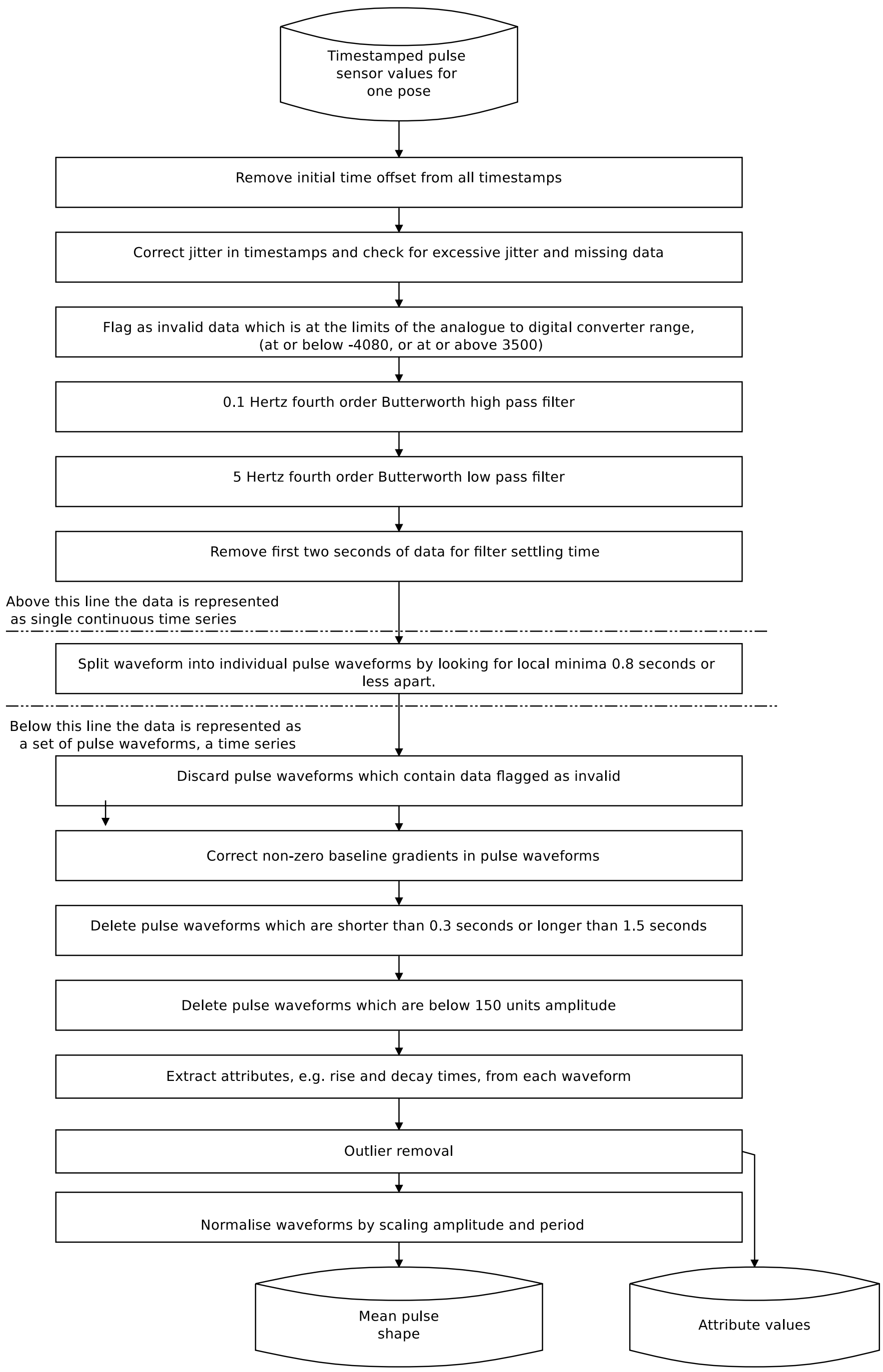


Figure 5-3: Principal processing steps for analysing pulse data.

A limited number of poses were used because of the likely difficulties for participants in holding fixed poses, particularly standing. The arm positions in each pose were made as similar as possible to each other to reduce the effect of arm position. The optimum LED brightnesses were set at the start of the run by working through a range of LED current limiting resistors and visually examining the pulse signal amplitude using the data recording program.

When participants changed between sitting, lying and standing poses two minutes elapsed before data collection to allow the baroreflex response to stabilise. No participant had consumed caffeine, alcohol or carried out strenuous exercise within an hour of their test run, except for participant 1 with a coffee 30 minutes beforehand. The measurements were made using both the wrist and fingertip sensors in the poses listed in Table 5.1.

The processing used the same offline software as in Chapter 4, followed by classification of the pulse waveforms using a multilayer perceptron. As before signal conditioning was by 0.1 Hz high pass and 5 Hz low pass 4^{th} order Butterworth infinite impulse response digital filters. Once the data was split into individual heartbeats, ones longer than 1.5 seconds or shorter than 0.3 seconds were eliminated as likely artefacts. Any which had an amplitude of less than 150 units were also removed, along with outlier removal of attributes when the multilayer perceptron classifier was used. The filtering stages are summarised in Figure 5-3.

5.6 Results

The wrist sensor produced acceptable quality data for all six participants, although some datasets were far noisier than others. The ability to modify the LED brightness allowed much larger amplitude pulse signals to be consistently produced. Age-related physiological effects such as the thinning of skin tissue did not cause a problem for photoplethysmography, making the fingertip data redundant.

Despite its role as a backup for the wrist, the fingertip actually proved more problematic since the signal declined proportionately more than at the wrist when the arm was hanging down. A smaller effect was seen if the tape holding the sensor to the fingertip was very tight, but in four of the participants the pose had to be repeated with a different fingertip current limiting resistor to obtain a usable signal. This was possible since the linearity of the sensor is good at low brightnesses as shown in Section 4.10.

As expected, the optimum LED brightness for the fingertip sensor was much smaller than at the wrist. Whilst the wrist LED current limiting resistor values were 1 kΩ to 2 kΩ the LED needed to be an order of magnitude dimmer to produce the same amplitude AC component, and the resistors used were 10 kΩ to 50 kΩ.

The pulse shapes showed similar types of variation as in younger people, but the variation was smaller. Two examples are shown in Figure 5-4. They were calculated by scaling all pulse waveforms to have the same period and amplitude and calculating the mean value for each time step. As before, the decay in the supine pose tended to be shallower in the normalised pulse curves.

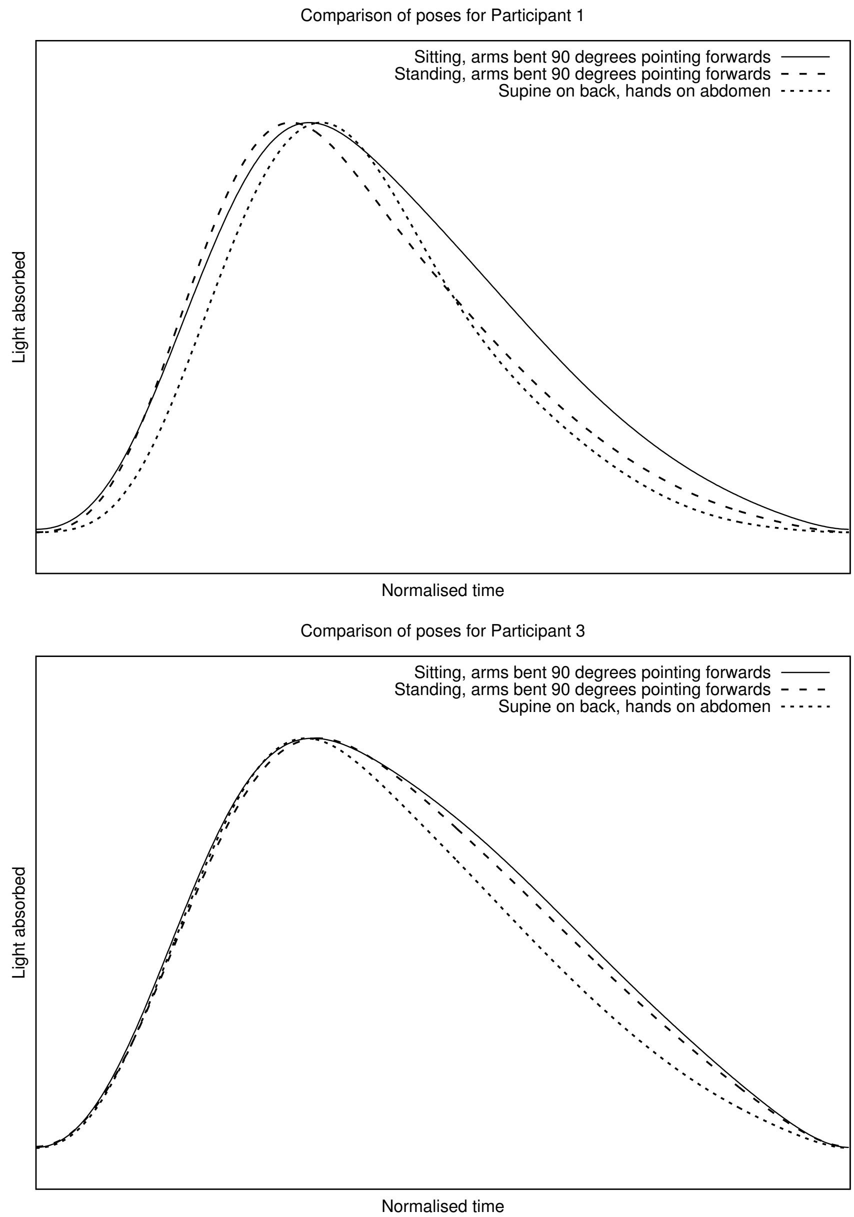
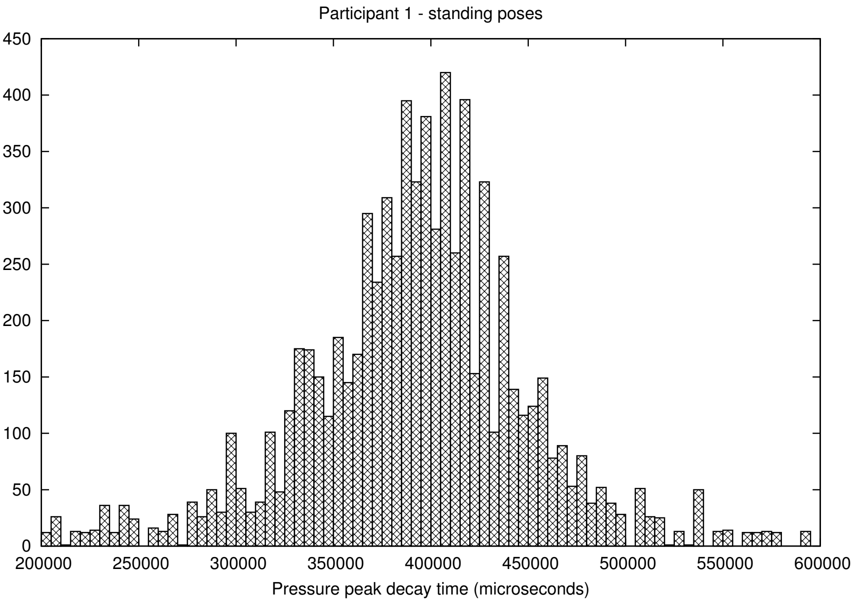
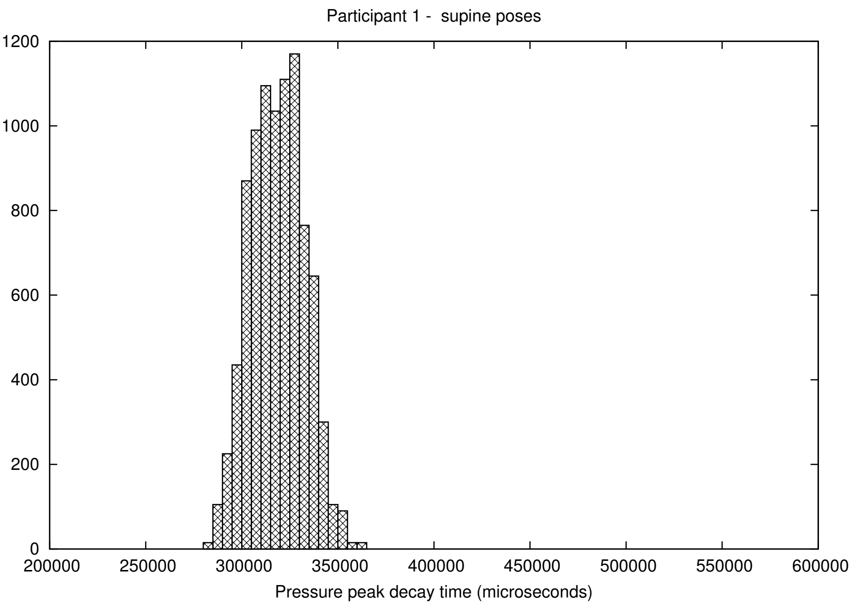


Figure 5-4: Pulse pressure peak shape variation with pose for two participants in sitting, standing and supine poses. Mean waveform shapes for normalised pulse curves. Note that the lengths of the curves are normalised. No outlier removal.

The supine pose values show a much smaller variation in attributes than the standing and sitting poses, confirming the previous study. Figure 5-5 compares the pressure peak decay times in the standing and supine poses.



(a) The two standing poses



(b) The two supine poses

Figure 5-5: Histograms of the decay times of the pressure peaks in the standing and supine poses. The much larger spread in the standing poses is in part due to motion artefacts. No outlier removal.

5.6.1 Repeated sitting pose

The first sitting pose, arms bent at 90 degrees and resting on the table or desk, was added to the end of the two supine poses to explore how the sitting pose attributes changed.

It was anticipated that the data for the second five minutes of sitting with the arm on the table at the end of the run would match the first carried out at the start of the run. However, this was not the case and there was much more variability than expected. Participants 3-6 showed little variation between the supine pose and the final sitting pose, as shown for Participant 3 in Figure 5-6. The change in pulse rise times and decay times was inconsistent – in some participants the final sitting pose rise time was much closer to the initial sitting pose rise time, and in others it was not, and similarly for the decay times. Figure 5-7 shows how the pulse decay times did not adjust between the supine and sitting pose in Participant 4.

5.7 Discussion

The pulse shape in different poses was measured in 6 participants, and the ability to change the LED brightness coupled with an understanding of the pulse sensor sensitivity allowed far better control of the pulse signal amplitudes than in the previous study.

The ease of measuring the pulse shape at the wrist showed that the improved sensor is more effective. The smaller changes in pulse shape are not unexpected since this was seen in the first study.

The variability of the pulse shape in the sitting pose was unexpected, particularly with the two minute wait following the participant sitting before data recording started. Participants 1 and 2 showed greater difference in pulse waveform shape between the sitting poses and the supine poses, than the other participants, as the shown for Participant 1 and 3 in Figure 5-6.

One possible explanation is hysteresis or lack of sensitivity in the supine to upright transition in the baroreceptor reflex. Participants 1 and 2 lay in the supine poses in an adjacent room to the one containing the table used for the sitting poses. When they changed from the supine pose to the sitting one they walked for ten or fifteen seconds to the table. The remaining four participants lay close to the table and to repeat the sitting pose stood up and sat back on the chair immediately. In all cases there was at least a two minute delay whilst the participant was sitting before data recorded started.

It is possible that the supine to sitting transition was not sufficient to trigger a large baroreceptor response in the last four participants. In the first two participants, blood pressure in the upper part of the body fell sufficiently during the walk across the room to cause a much larger response. There is some evidence for asymmetry in the response, Toska and Walløe

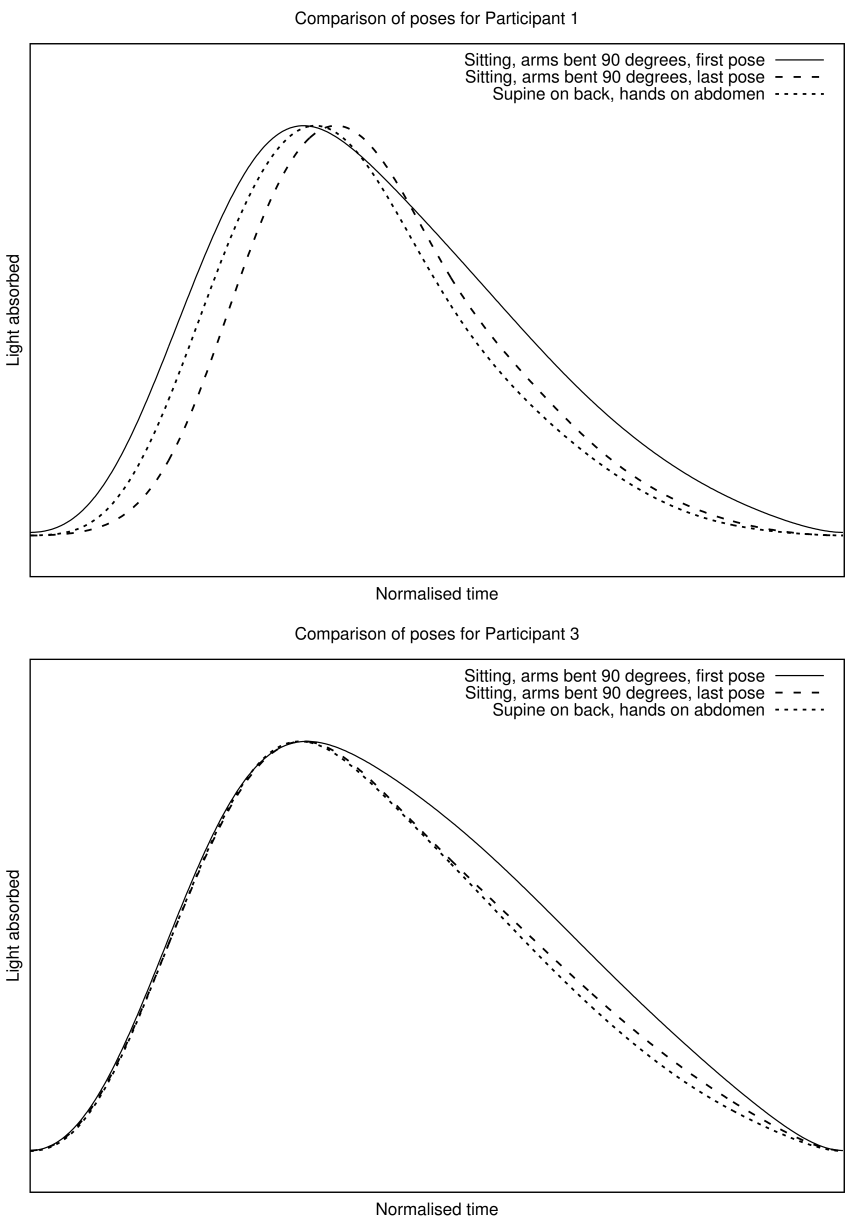


Figure 5-6: Mean normalised pulse waveform shapes for the initial and final sitting poses, with the shape for the last supine pose adopted immediately before the final sitting pose. Participant 1 shows a change in pulse shape between the supine pose and the following sitting pose, whereas Participant 3 does not. Participant 1 walked across a room between the supine and final sitting pose; Participant 3 stood up and immediately sat in a chair. Mean waveform shapes for normalised pulse curves (no outlier removal).

(2002) monitored the cardiovascular parameters of seven 22–24 year olds following transitions between 30 degree supine and head up positions using a tilt table and found that the cardiovascular system responded to the supine position three times faster than the head up position, with the latter taking up to 30 seconds before the baroreflex response was complete.

5.8 Classifier performance

As in the previous study a multilayer perceptron was used to classify wrist measurements taken in the first six poses, which contained approximately the same number of pulses in the sitting, standing and supine positions. This produced the results shown in Table 5.2, which reflect the improved signal amplitudes. The results at the fingertip, shown in Table 5.3, were superior to the wrist, as was expected.

Participant	Sex	Age	Median pulse amplitude	Total pulses	Correctly classified	Success rate	Kappa κ	$\sigma_{r,p}$ of rise/decay time ratio
1	F	79	1339	1643	1333	81%	0.72	0.09
2	M	79	1532	912	767	84%	0.76	0.08
3	F	77	1720	1775	1551	87%	0.81	0.08
4	F	84	1323	2361	1795	76%	0.64	0.10
5	M	74	882	1465	1064	73%	0.58	0.35
6	M	77	2026	1675	1068	64%	0.45	0.14
median		78	1436	1659	1201	79%	0.68	0.09
mean		78	1470	1639	1263	78%	0.66	0.14
sd		3.3	390	469	373	8.6%	0.13	0.11

Table 5.2: Results for the wrist sensor using five attributes with 6 poses; 2 each of classes sitting, standing, supine. Outlier removal for the five attributes used by the classifier enabled.

5.8.1 Identifying supine poses

A fall detector is intended to discriminate between the individual lying supine and upright poses. If the sitting and standing poses are treated as a single class, the data provided a good result using five attributes, as shown in Table 5.4.

The classifier categorised individual pulses, and it is likely that better results would be obtained by amalgamating the results from several pulses.

5.8.2 Additional sitting pose

This study differed from the previous ones in having a sitting pose following the last supine pose. Despite the closeness of the pulse shape in the final sitting pose to the supine poses the

Participant	Median pulse amplitude	Total pulses	Correctly classified	Success rate	Kappa κ	$\sigma_{r,p}$ of rise/decay time ratio
1	1598	1250	942	75%	0.60	0.08
2	969	978	894	91%	0.86	0.45
3	1057	1969	1934	98%	0.97	0.06
4	2688	1833	1531	84%	0.75	0.14
5	2740	1453	1209	83%	0.75	0.35
6	1696	1616	1148	71%	0.56	0.23
median	1647	1535	1179	83%	0.75	0.18
mean	1791	1517	1276	84%	0.75	0.22
sd	770	369	394	10%	0.16	0.16

Table 5.3: Results for fingertip using five attributes with 6 poses; 2 each of classes sitting, standing, supine. Outlier removal enabled for the five attributes used by the classifier enabled. In some cases the LED brightness on the fingertip needed adjustment.

Participant	Median pulse amplitude	Total pulses	Correctly classified	Success rate	Kappa κ	$\sigma_{r,p}$ of rise/decay time ratio
1	1339	1643	1630	99%	0.98	0.09
2	1532	912	911	100%	1.00	0.08
3	1720	1775	1729	97%	0.93	0.08
4	1323	2361	2307	98%	0.95	0.10
5	882	1465	1319	90%	0.80	0.35
6	2026	1675	1425	85%	0.67	0.14
median	1436	1659	1528	98%	0.94	0.09
mean	1470	1639	1554	95%	0.89	0.14
sd	390	469	467	6.0%	0.13	0.11

Table 5.4: Results for the wrist sensor using five attributes with the first 6 poses; 2 each of sitting, standing and supine. Classifying into supine and non-supine. This does not include the final sitting pose after the supine poses. Five features with outlier removal enabled.

classifier performance did not deteriorate greatly, as shown in Tables 5.5 and 5.6, although this may have been because the extra pose only increased the number of pulse waveforms by a sixth.

The most common misclassification is sitting as standing followed by standing as sitting, as shown in the confusion matrices for the participants, Table 5.7.

The results still suggest that this technique may be useful for fall detection, but more work is needed to understand the variability and to optimise the feature selection. In particular a supine pulse shape after someone has risen to a sitting pose would be fine, but retaining a sitting pulse shape after slipping off a chair into a supine posture would be less satisfactory.

Participant	Sex	Age	Median pulse amplitude	Total pulses	Correctly classified	Success rate	Kappa κ	$\sigma_{r,p}$ of rise/decay time ratio
1	F	79	1434	1904	1442	76%	0.63	0.08
2	M	79	1500	1070	801	75%	0.62	0.08
3	F	77	1889	2074	1803	87%	0.80	0.08
4	F	84	1576	2764	2161	78%	0.67	0.09
5	M	74	1056	1683	1151	68%	0.52	0.33
6	M	77	2156	1916	1224	64%	0.46	0.14
median		78	1538	1910	1333	75%	0.63	0.09
mean		78	1602	1902	1430	75%	0.62	0.13
sd		3.3	381	550	488	8.0%	0.12	0.10

Table 5.5: Classifier results for the wrist using all seven poses, including the sitting pose after the supine poses. The poses are classified into sitting, standing and supine with five attributes and outlier removal is enabled. Compare with Table 5.2, which has the first six poses only.

Participant	Median pulse amplitude	Total pulses	Correctly classified	Success rate	Kappa κ	$\sigma_{r,p}$ of rise/decay time ratio
1	1434	1904	1775	93%	0.85	0.08
2	1500	1070	979	91%	0.79	0.08
3	1889	2074	2005	97%	0.91	0.08
4	1576	2764	2643	96%	0.89	0.09
5	1056	1683	1459	87%	0.72	0.33
6	2156	1916	1540	80%	0.53	0.14
median	1538	1910	1658	92%	0.82	0.09
mean	1602	1902	1734	91%	0.78	0.13
sd	381	550	563	6.2%	0.14	0.10

Table 5.6: Multilayer perceptron results for the wrist using all seven poses, classifying into supine or non-supine with five attributes. Compare with Table 5.4, which has the first six poses only, lacking the sitting pose following the supine poses.

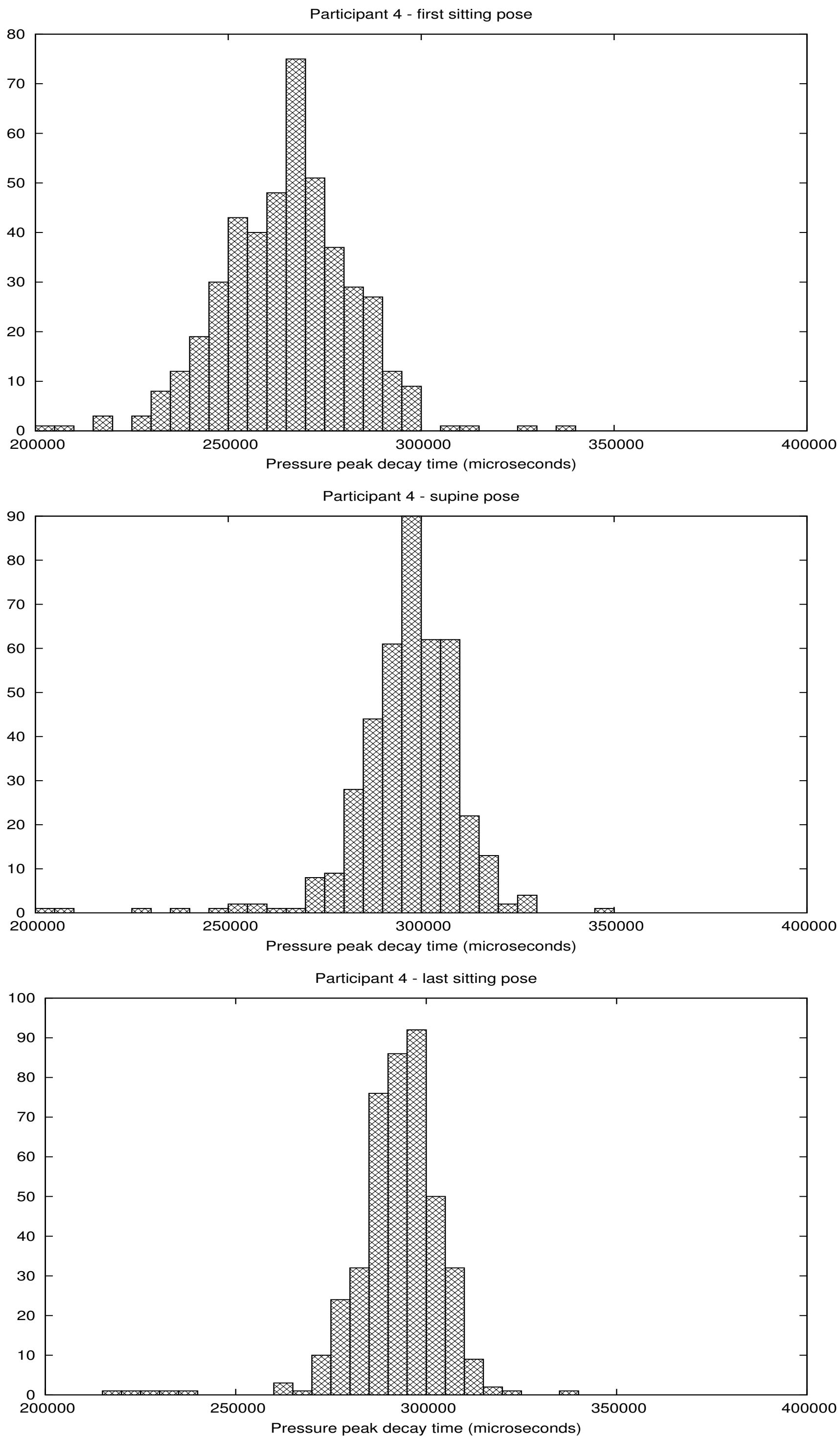


Figure 5-7: Pressure peak decay times for Participant 4 in the initial sitting pose, the last supine pose and the sitting pose following it. The pressure peak decay times did not return to the initial sitting pose ranges after the last supine pose. No outlier removal.

Participant 1, N = 1643			
	Classified as		
	Sitting	Supine	Standing
Sitting	337	9	158
Supine	0	590	1
Standing	137	5	406

Participant 2, N = 912			
	Classified as		
	Sitting	Supine	Standing
Sitting	224	1	72
Supine	0	297	0
Standing	72	0	246

Participant 3, N = 1775			
	Classified as		
	Sitting	Supine	Standing
Sitting	485	17	106
Supine	28	449	2
Standing	67	4	617

Participant 4, N = 2361			
	Classified as		
	Sitting	Supine	Standing
Sitting	562	30	227
Supine	21	723	1
Standing	270	17	510

Participant 5, N = 1465			
	Classified as		
	Sitting	Supine	Standing
Sitting	208	139	139
Supine	24	549	1
Standing	73	25	307

Participant 6, N = 1675			
	Classified as		
	Sitting	Supine	Standing
Sitting	185	115	202
Supine	41	482	16
Standing	121	112	401

Table 5.7: Confusion matrix for the multilayer perceptron classifier results using data measured at wrist with five attributes and attribute removal. This matrix is for the first six poses excluding the final sitting pose after the supine poses. The classifications which are correct are underlined.

5.9 Limitations of the measurements

The study used similar sensors and software as described in Chapter 4. However that work had led to substantial improvements in the the pulse sensor, offline processing and understanding of LED brightness issues which were responsible for the much better results in this study.

The sample was very small and unrepresentative of the wider elderly population. In common with most people aged 70 or more, all of the participants took some medication, and this was not controlled for. To exclude people who take medication would remove most of the likely fall detector population, although restricting medication taken before the study may have been beneficial. This was suggested by the Health ethics committee but would have burdened the participants by requiring the involvement of their GPs, but it raises larger questions around the effect of drugs on the pulse shape.

A smaller set of poses was used compared to the previous study, although probably representative of common poses.

The small number of attributes – the rise time, the decay time (and their ratio), and two representations of shape characteristics of the pulse – is a limitation. As in the previous study, the participants were relaxed throughout the test and it is likely that their cardiovascular system, and in particular the pulse rate, was not undergoing the changes which accompany psychological stress. This is very important as the pulse rate certainly changes with pose.

The baroreflex response was controlled for by having the individual wait for two minutes following sitting, standing or supine position change, but a real fall detector may activate before the response has completed.

The study only touched upon how the pulse shape varies when the same pose is adopted multiple times, but even so this was sufficient to identify it as an area which needs more work.

5.10 Conclusion

This study used a sample which was more representative of the target population for the fall detector. The results confirm the findings of the previous two studies, that determining body pose from pulse shape measurements taken at the wrist is a viable approach, although the extra sitting pose raised a question mark about small vertical changes in posture.

Nevertheless, the results are very encouraging. That they could be obtained using a relatively crude sensor, the limited effort in identifying suitable attributes and simple data processing steps are certainly grounds for cautious optimism. It should be remembered that the results presented here are for classifying single pressure pulse waveforms, and in a practical system combining the results from several waveforms would be expected to improve the overall reliability.

The results continue to point to a possible technique which could be used alongside accelerometry and other physiological measurements to identify falls.

Chapter 6

Designing a fall detector for people with dementia

6.1 Introduction

The previous chapters approached fall detection as a technical exercise, examining a technique which might be used to improve the efficiency of fall detection. However, a successful device needs to do more than address technical details. The needs of its users are wider than this, and include safety, comfort, desirability, economy and ease of use, all within the context of the users' own goals and abilities. This is the focus of this chapter and Chapter 7, which contain a design study for a fall detector for people with dementia.

The following section contains a short review of user centred design and its techniques, with particular reference to designing for people with functional impairments and its application to the design of the fall detector.

6.2 Literature review

To identify their requirements it is first necessary to identify the users. *Direct users* are those who actually use the product (Vredenburg et al., 2001), but there may also be *indirect users* who provide inputs to it, or use the outputs, without interacting with the product directly. This is an important consideration since other stakeholders must inevitably influence the design even though they may never set eyes on the device.

For example, Goodman-Deane et al. (2010) found that the commissioning clients funding or driving the design process themselves heavily influenced the design process since they are responsible for the initial problem definition (almost always specifying the target users) and the cost and time constraints. In addition, they often provide the initial information about the users and can also influence the process in more subtle ways, for example by their project reporting timetable and their feedback.

The direct users of the fall detector are not simply the wearers. The carer needs to have faith that it will work reliably, and it must be easy for them to handle – putting it on and taking it off of the wearer, receiving alerts from it, and determining whether it is working or not. Cost is a consideration, and it may be purchased by an organisation who will also have requirements for the device. It also needs to be easy to connect to the telecare network, cheap to manufacture and to dispose of at the end of its life.

The overall acceptability of a product to its users is a combination of many attributes, some of which are shown in Figure 6-1. Usefulness was traditionally split into utility and usability (Nielsen, 1993, page 25, citing Grudin, 1992). Utility is how well the functionality of the product is capable of fulfilling the need, whilst usability is how easy it is for people to actually get it to do so.

However, a third element, accessibility, has become increasingly important in recent years. This is the degree to which a wide range of people can use the product, including those with functional impairments (Wegge and Zimmermann, 2007). Whilst this might be thought of as part of its usability, for example Hertzum (2010) described *universal usability* as the challenge of making the product usable by as wide a range of people as possible, rolling together factors such as age, personal styles, values, knowledge, health conditions, income, and even environment – whether the lighting is bright for example, more often usability and accessibility are treated as separate albeit related concepts. Accessibility will be described next, because a system which is inaccessible to someone cannot be used by them, rendering utility and usability irrelevant (Fain, 2010).

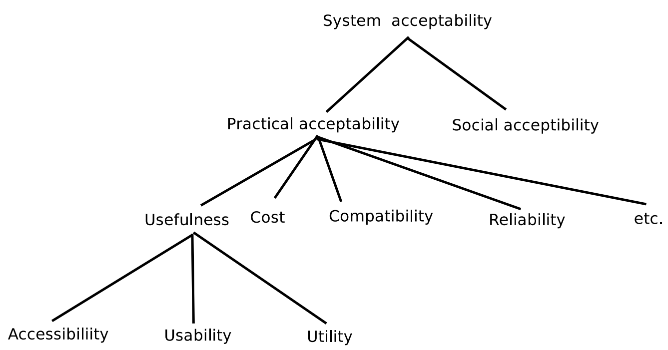


Figure 6-1: Attributes of system acceptability (Based on Nielsen, 1993, page 25, with accessibility added)

6.2.1 Accessibility

All of the wearers of the device will have functional impairments, and many of their carers will too. 21% of carers of people with dementia are aged over 65 (Alzheimer's Association, 2014) which means that age-related illnesses will be an issue for many of them. Combe et al. (2011) examined the characteristics of a typical central heating programmer in terms of the vision, cognitive abilities and dexterity needed to operate it. They estimated that 9.6% of people aged 16+, and 20.7% of people over 60, would be unable to use it because of its small and very limited set of controls coupled with a small and indistinct LED display controlling a complex set of functions. This has direct relevance to the fall detector – the device might at least need controls to turn it on and require some indication that it is working, and may need more sophisticated features such as the ability to cancel alarms.

Some fall detectors, amongst many similar small portable devices I have examined, actually have even worse controls. These can feature small concealed buttons which must be pressed a particular number of times, and respond with a certain number of LED flashes to indicate success or failure of the operation.

Inclusive design, often called *universal design* in the USA and *design for all* in the EU (Clarkson et al., 2003; Wegge and Zimmermann, 2007), is the principle that a product should be usable without modification by the greatest number of people of different ages, abilities and health conditions (Beecher and Paquet, 2005).

Inclusive design does not have to be ugly or compromise aesthetics. A good example of an attractive inclusive design is a door handle in the form of a lever instead of a round knob, since it is usable by most people, including those with limited grip or strength and even those without hands (Centre for Universal Design, 2006).

Disability is the result of a complex interaction between an individual's functional impairments and the world around them. The *medical model* views disability purely as a medical condition but this does not capture the reality from the individual's perspective. The alternative *social model* views it as the individual's experience of the interaction between their impairment and their environment (Homa, 2007; Ustün et al., 2003). For example, for a wheelchair user disability is in part defined by the inability to travel or move around easily if their environment lacks the necessary adaptions, and their disability is diminished if the environment is modified.

One widely used framework for classifying disability which combines these two different views is the World Health Organisation's ICF, the International Classification of Functioning, Disability and Health. It characterises an individual's disability in four different areas. Two of these relate to the medical condition, the anatomical and functional impairments, and the other two to the impact that they have on the individual and the support that their environment offers. The full model looks at nine different domains for the individual's ability to carry out tasks and interact with society, for example in areas such as self-care, cognitive abilities, and community and social life. For each of these their innate ability without help to function in these domains (their *capacity*) is considered alongside their ability with the assistance that is available to them (their *performance*). The classification also looks at environmental factors – barriers and facilitators – provided by the environment within five domains (Homa, 2007; Ustün et al., 2003).

6.2.1.1 Top down or bottom up?

The inclusive design philosophy can either take an overall bottom-up or top-down approach (Keates and Clarkson, 2004, page 60–62). Bottom-up approaches start with an existing product which is inaccessible to many people and modify it to improve its accessibility, whilst top-down designs modify a product designed for people with the most severe impairments and make it more usable for the wider population.

Neither approach is ideal, since they can only be taken so far. For example, a bottom-up approach extending the design of a television to make it much more accessible to people with limited sight or hearing is relatively easy but the simple adaptions needed would be useless for someone who is both profoundly deaf and blind, and instead the only viable approach would be to rethink the entire concept of a television (Keates and Clarkson, 2004).

Conversely, whilst top down approaches explicitly include those people with the greatest limitations, it is difficult to produce a product of interest to the wider community, and this inability to extend such products into a much larger market often destroys their commercially viability. Braille printers and robotic rehabilitation products have had very little commercial success because the inability to reach a mass market has held costs high and rendered them economically inaccessible even to many of the people who would most benefit from them (Keates and Clarkson, 2004, page 60).

The approach I have used throughout this thesis is bottom-up because it takes an existing design concept and modifies it to allow it to be used by a more impaired group. It is unlikely that this could produce a device accessible to people with the most severe dementia or carers with serious functional impairments. The alternative top-down approach risks producing a very specialised device unsuitable for those who have less severe dementia but are at more risk because of their greater mobility.

6.2.2 Usability

Usability is the optimisation of a product to be efficient, effective and satisfactory to use (Wegge and Zimmermann, 2007). ISO 20282, covering the ease of operation of "everyday" consumer products, highlights effectiveness as the most important of these because the most common tasks undertaken with consumer products are simple and quick and so improvements in satisfaction or efficiency will not have as much impact on the user.

It is not purely an attribute of the product in isolation, but depends upon who the users are, their goals and the environment in which it is being used (ISO, 1998). Nor is it isolated from other product attributes because it can easily affect them, in particular accessibility and even safety – several aircraft crashes in the 1940s were due to the poor usability of altimeters causing pilots to fatally misread them (Grether, 1949; Stanton and Harris, 2010).

Designers often unconsciously develop products for people just like themselves, with their own skills, abilities and values (Cooper, 1999; Keates et al., 2002; Hasdoan, 1996; Cardoso and Clarkson, 2012) since it can be difficult to internalise other people's abilities and mental models, and there is often a tacit assumption that everyone has the same thought processes (Floyd et al., 2008). It can also be tempting for them to evaluate the product based on their own understanding of similar products and their experience in using them (Hasdoan, 1996).

Since the designer is usually an expert in the product this actually works very well when the normal users are experts in the product too – for example the designers of professional quality climbing equipment are usually professional climbers themselves (Norman, 2004, page 82).

However, when the designer is not representative of the users then poor usability is often the result. One study of 20 different consumer electronics products found that roughly half of product returns were due to non-technical, consumer-related issues, such as the device not working as expected (28%) (den Ouden et al., 2006). Cooper (1999) similarly found that many software usability problems were caused by user interfaces designed to reflect the software architecture instead of the user's mental model of the task to be performed.

A poor understanding of the abilities of elderly people often causes problems in the design of consumer products (Keith and Whitney, 2009) and this can be particularly acute for assistive living devices where the designer has different physical abilities to the users. This problem has led to an approach to accessibility called *transgenerational design* where particular emphasis is put on accommodating the physical and sensory impairments associated with age (Woudhuysen, 1993).

6.2.3 Aesthetics

Many assistive living devices fail because they poorly match their users' lifestyle or demographic characteristics such as gender (Ravneberg, 2012). They are frequently designed without any consideration of aesthetics, resulting in such ugly objects that they repel their users (Newell et al., 2010). The root cause is often that the power in the marketplace resides with the service providers, with manufacturers perceiving them as the real customers, with the direct users of the technology treated as passive and impotent recipients (Ravneberg, 2012). One consequence is that users can feel stigmatised by assistive devices, which in itself can discourage people from using them or by association raise concerns that they will be moved to residential care because of the reduction in independence that they signify. Holliday (2012) quotes one Telecare lead on a fall detector:

> "We show them the equipment, they see it and they just say "I'm not wearing THAT, I'll be fine"" (Holliday, 2012)

This need not be the case. Newell et al. (2010) pointed out that over the last 200 years spectacles have developed from purely functional assistive living devices to stylish fashion statements, whilst walking sticks have travelled in the opposite direction, from attractive beau monde accessories to their current place as – in many cases – ugly medical aids. Needless to say inclusive products should not segregate or stigmatize users (Story et al., 1998).

6.2.4 Design process models

Most design models can be viewed as a sequence of large scale stages each of which may be sub-divided into a series of individual activities (Wynn and Clarkson, 2005, citing Blessing (1994)). For example, ISO 13407:1999 *Human-centred design processes for interactive systems* (ISO, 1999) provided a typical model process for design made up of four stages, each of which will contain several distinct activities.

1. Understand the context in which the product sits
2. Define the requirements for the product
3. Produce the design solutions
4. Evaluate the solutions

There is a clear divide between the first two stages, which are concerned with defining the requirements, and the second two stages which form the solution. Another user centred design process model, the Double Diamond Design Model (Design Council, 2007) makes the distinction between the two stages even clearer by mandating a requirements document as a product of stage 2.

Many models concentrate on the last three stages, rolling understanding the context into defining the requirements, for example Blessing et al. (1995). There are many models because of the huge range of different viewpoints (Design Council, 2007) and approaches.

The process can be purely linear, with each stage being concluded before the next is started, or have degrees of iteration in which stages are repeated. The reason for repeating a stage is to utilise new information gathered during an earlier iteration of it or a subsequent stage (Wynn and Clarkson, 2005). Iterative approaches are usually preferred, at least in the early stages of the design (Norman, 2013, page 234), because it is hard to retrospectively fix deficiencies made in earlier stages – if the product requirements are too rigidly specified early on then they are difficult to modify if additional or different requirements become apparent later in the process (Royce, 1970).

For example, a fall detector system might be specified to have an audible alarm for the carer, only to require a rethink when evaluation of the product finds it unusable by a profoundly deaf carer. This may require a change in the original requirements which can be cumbersome and perhaps require significant rework of most of the later product design stages.

Whilst process models show a clear delineation between stages, in practice this is usually only an approximation since stages are often poorly defined and applied unsystematically (Goodman-Deane et al., 2010).

6.2.4.1 Product centred versus user centred approaches

The fall detector must fulfil the needs of the carer and the wearer, and at the same time accommodate the physical limitations imposed by its mechanical and electronic components. Systematic engineering design processes make it easier to produce an optimal design because they facilitate a structured search through many possible solutions to find the most appropriate ones (Motte, 2008).

Some design processes are primarily driven by prioritising the attributes and goals of the users, to which engineering expertise is added to produce the viable product design; whilst others treat the design process as purely one of engineering the product to meet functionality requirements. The first approach is an entirely user centred one, whilst the second is entirely product-centred (Keates and Clarkson, 2004, page 147). The majority of product design processes lie somewhere between these two extremes.

Whilst product-centred approaches are antithetical to accessibility (Keates and Clarkson, 2004, page 147), they are perhaps suited to well-specified components and sub-assemblies which do not interact directly with the user. Ulrich and Eppinger (2012) describes these as technology-driven because whilst usability might be a factor, technical performance is paramount in driving the consumer's product selection and user preferences are limited to external and superficial attributes. Whilst they gave computer hard disk drives as their example, this is also true of many standardised commodity items such as ball bearings and surface mount resistors.

The fall detector will contain many examples of this type of component, hidden from the user but meeting precise electrical and mechanical specifications for minimum cost and maximum reliability. This is not to say that users can be entirely ignored in their design since people will be involved in the handling, assembly, maintenance and disposal of these parts and so, for example, ease of identification and handling must be addressed but it is the engineering considerations – often the ability to be processed by automated assembly machinery – which drive their design.

Nevertheless, many authors consider user centred approaches as the natural and obvious way of designing products (Vredenburg et al., 2001) and it is now considered unusual for users not to be involved in design (Binder et al., 2008).

The overall design of the fall detector must certainly involve users to a great degree because usability and accessibility are key design issues, since the device is to be worn by someone with serious cognitive difficulties, and the carer with whom the device will also interact may have age-related sensory and motor impairments. It is only people who have experienced the realities of dementia who have the necessary specialist understanding of what is required.

User input into the design of assisted living products is particularly important as they have a poor reputation – Hocking (1999) suggested that up to 56% of assistive technology devices are abandoned by users. Although sometimes this occurs because the user's condition changes, often it is because the device is unreliable, ineffective, hard to use or even just very ugly. Hocking (1999) suggested that 15% of assistive technology devices are *never* used.

As examples of the types of fundamental problems with many devices, Gardner et al. (1993) described several commercially available products intended to help elderly people with activities of daily living, all of which had very serious usability defects. In some cases the product simply didn't work – for example a device which allowed weeds to be removed without the user having to bend down was completely useless for the task.

Even those which did work could present serious usability problems for the target population. Out of many examples, the authors selected a walking stick with an attachment for picking up small objects. Whilst it was usable by able-bodied people, someone who needs to lean on a walking stick to stand could not simultaneously manoeuvre it to pick up an object.

Many products had serious quality or safety defects, such as a step stool whose design encouraged people to overbalance on it. Often the defects were the result of seemingly minor design decisions, and in all cases proper consultation with users would have prevented the problems.

Design decisions can also have ethical implications which can often only be addressed by involving users in the design process. For example, some wander alarms are deliberately designed to be difficult to remove (Mahoney and Mahoney, 2010), a design decision which overrides the wearer's choice in the matter. There are ethical issues around the design of the fall detector, particularly for someone with dementia, as the wearer needs to make and maintain informed consent. An unintended consequence of the device might be to reduce the amount of human contact that they experience if the carer feels more comfortable leaving them alone, and perhaps an increased risk of falling if too much reliance is placed on it (Ganyo et al., 2011).

However, there are obstacles to user centred design. Whilst the great majority of studies show a positive impact for user centred design, one study which did not show a benefit is Heinbokel et al. (1996), which was a longitudinal study of 29 software projects. This concluded that user participation was correlated with poor overall success as judged by the software developers, lack of innovation, low team effectiveness and software which could not be easily modified and thus harder to maintain. One reason advanced was that users tended to propose major changes late in the development cycle which was disruptive when most of the software had been written. This happened both because users tended to develop more sophisticated ideas over time and because they often unpredictably changed their minds and demanded radical changes, perhaps as a result of seeing a competitor's product.

Another, quite different, reason was that users feared that the software would lead to poorer working conditions, even job losses, and so were unwilling to constructively engage. Finally, the user orientation of the designers led them to be more ambitious than they otherwise would be which caused more stressors on the project, such as increasing workload and the number of decisions reviewed, and reduced team effectiveness. None of this is to say that user centred design leads to a worse product from the perspective of users, but it does point to user involvement making the project harder, more uncomfortable, and more expensive for the developers. These conclusions were reinforced by another systematic review of 87 software projects which found positive outcomes in 68% of projects but negative ones in 14% (Bano and Zowghi, 2015).

Vredenburg et al. (2002) reported that nearly half of the 103 designers who responded to a questionnaire survey believed that user centred design increased product development costs, in contrast to about a quarter who believed it reduced them. Similar numbers agreed that it increased the amount of time needed. The attitude of the commissioning client is usually a very strong factor in whether a user centred approach is used (Goodman-Deane et al., 2010) since they control the timescales and budget (Sims, 2003, page 58).

Different design methodologies involve users to varying degrees. At one end of the user-involvement scale are techniques which fall short of user centred design such as the Agile methods for developing computer software which involve users through feedback from an iterative series of prototypes (Sommerville, 2011, page 57), but lack the detailed user focused research prior to the construction of prototypes (Chamberlain et al., 2006).

At the other end of the scale, Participatory Design goes much further than user centred design by recruiting users as full members of the design team, where they actively make design decisions alongside the designers (Sanders and Stappers, 2008). This differs markedly from user centred design methods where there is a clear divide between designers and users, with the latter treated more as subjects than colleagues by the designers and consequently having less influence over the outcome than the designers (Sanders and Stappers, 2008).

6.2.5 User centred design

User centred design is an umbrella term for both a philosophy for addressing problems of usability by involving users in the design of the product, and several more or less well-defined specific methodologies for doing so (Chamberlain et al., 2006). The design process incorporates the following distinctive features (Vredenburg et al., 2002; International Standardisation Organisation, 2010).

- Representative users of the product play an active role throughout the product development cycle. The mechanisms and degree of involvement in different stages of the design varies with the product and specific methodology.
- The users provide the designer with an explicit understanding of themselves, their goals and environment.
- The users' goals are decomposed into the actual tasks which need to be performed with the help of the users.
- The design process is iterative with repeated evaluation cycles in which feedback from prospective users is at the core of the evaluation.
- The design process incorporates the entire user experience, not just the usability of the product. This means that the documentation about the product, the support services and even the product packaging are considered part of the design.

- The design is multi-disciplinary, involving product design and engineering, thus addressing the full range of form to function simultaneously.

The effect is to place the users' experience at the centre of the design process, around which all other factors in the product design revolve.

However, user centred design is not just blindly following the requests of the users, because whilst they are well placed to identify design defects they are often unable to propose viable alternatives (Kotamraju and van der Geest, 2012), a view neatly encapsulated in Henry Ford's apocryphal comment "If I had asked people what they wanted, they would have said faster horses" (Vlaskovits, 2011, discusses the mis-attribution).

This can sometimes result in conflict between the opinions of the designers and the users, with the usual result being that designers override the views of the users (Steen, 2011). A second important tension in user centred design is obtaining the correct balance between research and development – avoiding the costs of obtaining an excessively detailed understanding of the users and their goals, but not undertaking product design without having sufficient information (Steen, 2011).

Historically user centred design grew out of work by Donald Norman in the 1980s at UCSD and popularised in a 1986 collection of papers *User Centred System Design: New Perspectives on Human-Computer Interaction* (Abras et al., 2004; Norman and Draper, 1986) which he co-edited with Stephen Draper, a UCSD colleague. This was followed by *The Psychology of Everyday Things* (Norman, 1988), which proposed designing products which explicitly took human psychology and behaviour into account.

The book suggested a set of seven guidelines for good design. In particular a product should be designed so that it feels natural to use it correctly. The appearance of a product can be designed so that its use becomes intuitive, which Norman called an *affordance* (Norman, 1999), redefining a word invented by Gibson (1979) to mean the possible ways of interacting with a particular object, or preventing it from being used incorrectly, which Norman termed a *constraint*. Examples included cooker controls whose layout mimics that of the hotplates which they control, and door handles which provide unconscious cues about whether they are to be pushed or pulled. Nevertheless, by stressing the importance of properly researching the needs and behaviours of users, Norman was proposing that they became central to the design process (Abras et al., 2004).

6.2.6 Implementing user centred design

There are many tools and techniques which can be used in each stage of the design process, and a selection of common ones in shown in Table 6.1. Some of them involve the designers only, others use input or interaction with prospective users.

A toolkit called USER*fit* is an attractive tool for designing assistive technology since it is designed specifically for this purpose to ensure that the appropriate issues are addressed (Melchior et al., 1996c,a). A key goal of USER*fit* is to make the design issues clear in the process summary documentation as a way of ensuring that the assumptions which the product designers made about users and technology were properly justified (Poulson and Richardson, 1998). It was developed as part of the EU-funded USER (User Requirements Elaboration in Rehabilitation and Assistive Technology) project in the 1990s (Poulson and Richardson, 1998).

USER*fit* provides suggestions of techniques for involving users for each each stage in developing assistive living products, shown in Table 6.2, and guidelines for the design of products. It suggests the same techniques for engaging with users to produce a description of the product and its requirements as for the functional specification of the device. In the table these two design stages have been split to map more closely onto the ISO13407 model.

The table also shows the techniques recommended by (Nielsen, 1993, page 224) in his book on usability engineering. Nielsen did not categorise the project stages in the same way as USER*fit*, for example he specified “task analysis”, “early design” followed by “iterative design” and so the table attempts to fit his methods into the USER*fit* stages.

6.2.6.1 Understanding the context

Many design process models combine understanding the context with forming the requirements. Goodman-Deane et al. (2010) found that designers favoured informal techniques which could be casually applied over more formal and structured ones. This was particularly true of the earlier stages of the design.

USER*fit* (Melchior et al., 1996c) sub-divides understanding the context into understanding the environmental context and understanding product environment, for which the authors recommend using empathic modelling, brainstorming and group discussions. Activities which should be done in this stage according to other user centred and inclusive design processes are shown in Table 6.1.

Empathic modelling allows designers to start to understand the difficulties of people with physical impairments. Capability-loss simulators reduce the sensory perception or the movement of the designer to the level of someone whom they might be designing for (Cardoso and Clarkson, 2012). The simulators can be physical aids such as glasses or garments which limit the user’s sight or movement respectively, or video, photo or audio processing software which

Source	Understanding the context	Defining the requirements	Specification	Test (and follow up)
USER*fit* (Melchior et al., 1996c)	Empathic modelling Brainstorming Group discussions	User Mapping Direct observation Activity diaries Questionnaires Interviews Group discussions Empathic modelling Expert opinions	Task analysis Direct observation Activity diaries Questionnaires Interviews Group discussions Empathic modelling	User trials Direct observation Questionnaires Interviews Group discussions Field trials
Usability Engineering (Nielsen, 1993)	Performance measures Thinking aloud Observation Questionnaires Interviews Focus groups	Heuristic evaluation Thinking aloud Focus groups	Heuristic evaluation Thinking aloud Focus groups	Performance measures Observation Questionnaires Focus groups Logging actual use User feedback
Human Centred Design (Norman, 2013)	Observation	Brainstorming	Brainstorming	Observation
Inclusive Design Toolkit (Cambridge Engineering Design Centre, 2009)	Observation Needs list User journey	Observation Personas		Expert opinions User trials

Source	Early stages	Later stages
Common user centred design activities (after Goodman-Deane et al., 2010)	Examination of the designer's own behaviour Visualisation Producing sketches and other graphical representations	
	Informal observation Examination of competing and similar products Literature review and desk research Direct contact with users Observation of use cases Discussion within design team and personal reflection Brainstorming Scenarios, personas and use cases	Prototyping and modelling Feedback from users, experts and design team Drawing up detailed technical specification

Table 6.1: Design activities suitable for user centred design

reduces the resolution of a media clip to mimic the perception of someone with impaired sight or hearing (Clarkson et al., 2007).

The physical simulators range from simple devices, such as blindfolds (Kouprie and Visser, 2009) and foam earplugs (Cardoso and Clarkson, 2012) to elaborate and costly equipment such as whole body restricted movement simulators. Examples of these are the Third Age Suit developed in the 1990s to simulate the restricted movement of elderly car drivers and the Osteoarthritis Suit simulating the movement problems of people with arthritis (Cook et al., 2009).

One reason for using these techniques rather than asking users is cost – user involvement is both costly and time consuming (Cardoso and Clarkson, 2012). Simulators can be useful for evaluating ideas and designs when users of the product are not present, and are a key part of some user centred design processes (Cardoso and Clarkson, 2012). For example, the Empathic Design methodology allows the designer to understand the needs of the user on a behavioural and experiential level through experiencing the product as the user (Kouprie and Visser, 2009).

From a practical point of view they require little planning and can be used informally, although the most sophisticated devices are costly. Whilst they give some understanding of what it is like to have a physical impairment, they cannot do this for cognitive impairments, nor do they show what is it like to constantly live with it (Cardoso and Clarkson, 2012). They restrict movement by externally restraining it, rather than reducing the capacity of muscles and joints that facilitate it, and furthermore any observers gain little appreciation of the problems faced by the wearer (Cardoso and Clarkson, 2012; Hitchcock and Taylor, 2003).

Focus groups, brainstorming and group discussions are broadly similar activities strongly recommended by several design methodologies. The groups can include users, helpers of those users, designers, and domain experts. Whilst brainstorming is intended to generate ideas, other techniques such as focus groups try to generate agreement about particular issues (Melchior et al., 1996b, page 80–89).

Focus groups are particularly important for obtaining prospective user feedback and are very common in the early stages of the design process (Goodman et al., 2012, page 142). They are moderator-led discussion amongst a group of individuals who have been assembled to examine a specific issue or concern (Bruseberg and McDonagh-Philp, 2002). They provide qualitative information based on the participants own desires, motivations, experiences and opinions. They produce similar information to interviews but are much more efficient in terms of the researcher’s time (Goodman et al., 2012).

The discussions can be time-consuming, and selection of suitable participants to obtain a broad range of representative views can be difficult but they can provide useful data for even the smallest projects (Bruseberg and McDonagh-Philp, 2002) and the interaction between participants may provide useful insights (Nielsen, 1993, page 214). They have limitations though – they rely upon self-reported beliefs and perceptions so that participants cannot describe what they really do in certain situations, only what they think they do; nor are they good at finding what changes people will in practice find useful or the impact of different design trade-offs. They typically contain between 6 and 8 people – having less than six people impedes discussion and limits the range of perspectives (Nielsen, 1993, page 215) and a single session can discuss about four main topics (Goodman et al., 2012).

There are a range of techniques used for these discussions, for example Newell et al. (2010) has persuasively argued for the use of professional actors staging vignettes to prompt discussion amongst prospective users, and also to stimulate and moderate discussions between designers and users whilst acting within character. Marquis-Faulkes et al. (2005) used video clips to facilitate discussion amongst older users about the requirements of a fall detector, for example, and live actors or audience members playing out small vignettes have been used for other types of product (Salvador and Howells, 1998; Sato and Salvador, 1999).

The USER*fit* manual (Melchior et al., 1996c) advises that if the group contains participants with cognitive impairments then participants should work in pairs so that only one of the pair has to write down the ideas. It also suggests that care be taken if there are elderly participants to ensure that they have sufficient time to produce their ideas.

Thinking aloud is a technique in which a user undertakes a task whilst constantly verbalising their thoughts. Nielsen (1993) is extremely enthusiastic about thinking aloud, suggesting that it "may be the single most valuable usability engineering method" (Nielsen, 1993, page 195). It is common used in both cognitive psychology and usability engineering, although the goals differ in the two areas since in psychology the emphasis is on internal cognitive processes whilst usability testing focuses on the user's interaction with the product or application (Krahmer and Ummelen, 2004). There are several ways of using this technique, most of which attempt to minimise the interaction between the user and the observer (Nielsen, 1993, page 199).

Classical thinking aloud (Hertzum et al., 2009) is a formal procedure widely used in experimental psychology. Developed by Ericsson and Simon (1980), it is based around a rigorous theoretical framework in which *Level 1 Speech*, speech produced directly from the thought processes accompanying the task with the minimum of cognitive processing, is considered the most valuable. Also of value is *Level 2 Speech*, the mental representation of the processes, perhaps in the form of abstract concepts or images, is translated to speech but no further cognitive processing done. In contrast, *Level 3 Speech*, which has been filtered internally or contains inference or reflection, is considered so unreliable that it should be discarded. To maximise the amount of Level 1 and 2 output, the participant is encouraged to talk constantly and if they fall silent then the only prompt should be "Keep talking" (Ericsson and Simon, 1980).

Thinking aloud is used much more informally in usability testing (Hertzum et al., 2009), with the observer asking the user questions and probing for information. This Level 3 Speech would be considered unreliable according to Ericsson and Simon (1980). The less formal approach has been criticised as lacking both rigour and theoretical foundation (Krahmer and Ummelen, 2004) and likely to focus on problems with the product that the user has consciously discovered rather ones due to unconscious behaviour. However, there are several reasons why the rigorous technique is less appropriate for usability testing, for example there is more uncertainty and complexity in interactions with products than in most psychological experiments, and with the user often role-playing clarification is often needed about their role. In addition, it is the participant who is being studied in experimental psychology, whilst in usability testing it is the product, with the participant's role being to provide information about it (Boren and Ramey, 2000). Thinking aloud is not a natural process and a practice session is recommended (Ericsson and Simon, 1980), or at least a demonstration (Nielsen, 1993, page 197).

As a user centred activity, thinking aloud generates more negative comments about specific aspects of a product than interviews or questionnaires, whilst the latter are better for generating a wider range of less detailed information on usability issues (van Velsen et al., 2007).

If a representative sample of users is hard to recruit, then Nielsen (1993, page 199) recommends *retrospective testing* to maximise the information obtained from a test. One technique is for the user to view a video recording of their thinking aloud test session, adding extra reflective comments. They can also perform the test in silence and then verbalise their thoughts whilst watching it (van den Haak et al., 2003). This has additional benefits, such as allowing the user to focus completely on the task and capturing higher-level reasons for problems, although perhaps at the expense of introducing bias in their verbalisation from causes such as forgetfulness or not wishing to appear incompetent (van den Haak et al., 2003).

Observation is used to find out concrete information about how and why people actually do things, which can be very different to what they believe, or remember, that they do (Goodman et al., 2012, page 211–242). A much more immersive extension to observation is *ethnography*, an approach taken from the social sciences where it covers a broad range of qualitative techniques (Steen, 2011), and would be called *ethnomethodologically-informed ethnography* (Crabtree et al., 2012, page 159).

The critical difference between observation and ethnography is the holistic approach of ethnography with an analysis of the behaviour of participants from social and cultural perspectives, even using language which they themselves use and understand (Crabtree et al., 2012, page 159). In this way it looks beyond the product's purpose in achieving a narrow functional goal, and instead considers its various roles within a rich social tapestry of personal goals, interpersonal relationships and culture. To obtain this information participants must be observed in the normal environment where they would use the product, and it requires much more than passive observation, with interactions between the researchers and the participants to properly understand why they perform actions in particular ways, along with feedback from them to confirm or refute the researchers' assumptions.

Interviews permit open-ended questioning to provide qualitative detail. They are very effective in exploratory studies to provide initial information about requirements and context (Nielsen, 1993, page 211). They can be conducted in person, or remotely – usually over the telephone. Whilst telephone interviewing may reduce interviewer-induced bias, in-person interviews are far better for covering complex issues (Shuy, 2001). They are also much more comfortable for the interviewee if the interview lasts more than 20 minutes and for older people who may have hearing impairments (Shuy, 2001).

Questionnaires by contrast require less effort per user for the designers although they may present difficulties with disabled or infirm participants, for example if they have poor eyesight. In these cases they may take the form of highly structured interviews, with the interviewer providing a verbal interface to the questionnaire and recording the answers. However, questionnaires generally provide much less rich qualitative information, although are usually a better source of quantitative data. In particular, whilst Likert scales can point to problem areas, they do not provide sufficient detail to properly understand the issues (van Velsen et al., 2007).

Since interviews and questionnaires form the backbone of qualitative research in the social sciences there is a vast amount of literature available on techniques and pitfalls, for example the limited duration of an interview may make a participant formulate opinions which they had not previously held or held only weakly (Myers and Newman, 2007), or equally limit the amount of information which can be gathered.

Personas are elaborate descriptions of fictional individuals who use the product. Each persona represents a class of archetypal user, with a realistic name and personal characteristics to flesh it out. These usually include their age, occupation, responsibilities and soci-economic status along with more individual ones such as educational achievements, likes and dislikes (Wallach and Scholz, 2012; Cooper, 1999).

They were originally proposed by Cooper (1999) for software user interfaces design, to replace abstract and overly flexible "users" in the minds of software developers with concrete images of people that the developers could relate to and having well-specified skills, goals and characteristics. Personas have since been extended outside of software design and their use is commonplace in inclusive design and product development generally (Miaskiewicz and Kozar, 2011; Clarkson et al., 2007; Wallach and Scholz, 2012).

Cooper warned *against* using real people to avoid focusing on their own quirks and peculiarities, so the persona is usually an aggregate of the features of several different people. Cooper stressed that whilst personas should be based on ethnography, and describe a typical user, detail is more important than accuracy (Cooper, 1999, page 129), since a persona is a very specific and stable mental model of a user with a clear set of requirements which cannot be bent around product design obstacles or clouded by ambiguity.

Whilst this makes designers adopt an attitude of constantly considering the user, a concept called *user orientation* (Heinbokel et al., 1996), this falls far short of user participation and can cause obvious problems with authenticity. A serious criticism of personas is that whilst many are grounded in reality, some just reflect the designers' own opinions, prejudices and stereotypes ("the designer's imaginary friends" (Saffer, 2005), quoted in Massanari (2010)), and can even be inventions created to justify specific design ideas (Floyd et al., 2008).

Scenarios are short descriptions of interactions between users or personas and the product. They became popular in the early 1990s following the work by Jacobson et al. (1992) on use cases. Scenarios can be used without much emphasis on personas, and predate them as an articulated concept by nearly twenty years (Holbrook, 1990; Hooper and Hsia, 1982). In Cooper's model they are vignettes involving a persona fulfilling some goal by interacting with the product (Cooper, 1999). The interaction covers much more than operating the product as they can also capture the interaction from the persona's emotional, social and cultural perspectives (McCarthy and Wright, 2005). Hence, the reasons why the persona acts in a particular manner are as important in the description of the scenario as the actions that they perform.

An innovative variation on this approach is *pastiche scenarios* (Blythe and Wright, 2006), in which an existing fictional character with appropriate characteristics is inserted into a scenario where they interact with the product to provide vivid accounts, for example how Bridget Jones might record her subjective experiences of her iPod in her diary (Blythe et al., 2005).

User journeys are a textual or graphical representation of a scenario, in which the persona (or real user) undertakes a sequence of 4–12 steps during which they interact with the current or potential product (Mears, 2013).

Needs lists are recommended by the Inclusive Design Toolkit, and are categorised lists of the requirements of the product. They link specific requirements to specific users and allow prioritisation of the requirements (Cambridge Engineering Design Centre, 2009). The format suggested by the Toolkit is "As a *role description* I need *need description* so that *reason*" (Cambridge Engineering Design Centre, 2009).

6.2.6.2 Defining the requirements

There are a some techniques which can be used to understand the user's needs and thus help determine what features the product should have.

User mapping is a simple technique for categorising stakeholders. Normally done as part of a workshop, it consists of listing the users and their goals, and from that the costs and benefits they are likely to incur (Melchior et al., 1996c). The USER*fit* manual cites Eason (1988) as the source for this task. He named it *user population mapping*, which is perhaps a better name since it is less ambiguous as several different mapping techniques (such as user journey mapping) are common in product design.

Activity diaries allow users to record activities or events on paper, online questionnaires or even video diaries (Melchior et al., 1996b, page 53-54). They range from unstructured open formats where the user writes the time of a significant event along with a prose description, to highly structured questionnaires. They are usually filled in when the event occurs, but can sometimes be done retrospectively at certain times of the day if the events are rare but this usually relies upon the user remembering them. A typical study has about ten participants recording over seven days (Goodman et al., 2012, page 243–247).

However, activity diaries are often incomplete, either missing events, or stopping after a shorter period than required (Crosbie, 2006), and different users will provide varying levels of detail. Since unstructured descriptions can be hard to interpret or lack critical pieces of information such as the text of an error message, (Melchior et al., 1996b, page 56) recommends structured questionnaires over more open-ended formats.

6.2.6.3 Specification

Guidelines are widely recommended for assistive design and there are many different guidelines documents available, some formal and others less so.

Amongst the more formal ones are various British Standards on disabilities and assistive living Associates (2013), such as BS 8300:2009 (BSI, 2009) on the built environment which, for example, gives detailed dimensions for items such as handrails and on-street parking bays. Others sets of guidelines include ISO/IEC Guide 71:2001 (ISO, 2001) for guidelines to consider when creating new standards, and even ISO/TR 22411:2008 ISO (2008) which contains guidelines on applying these guidelines.

There are many less formal sets of design guidelines, for example, Greasley-Adams et al. (2012) provided guidelines for adapting the built environment to benefit people with impaired sight or dementia, for example:

> "Doors of a different colour to that used for other rooms help people identify the location of the bathroom. Supplementing this with appropriate signage or pictures is helpful as some people may not always be able to remember the significance of door colours." (Greasley-Adams et al., 2012)

Design guidelines are also very common outside of assistive living, usually targetting specific aspects of product design such as user interfaces, for example Ben Schneiderman's Eight Golden Rules of Interface Design (Schneiderman and Plaisant, 1987) and Jakob Nielsen's Ten Usability Heuristics (Nielsen, 1994).

6.2.6.4 Testing

Testing takes place with prototypes and eventually with the final product, and is a core process to user centred design with its philosophy of iterating through several generations of product design.

Prototypes do not have to be physical objects even if the product will be, but are often just sketches or very basic mock-ups in the early stages. A prototype which broadly implements all of the functionality of the product but in a very shallow manner is called a *horizontal prototype* whilst one which implements a small part of the complete functionality in detail is called a *vertical prototype* (Floyd, 1984; Nielsen, 1993, page 94). In the earlier stages simpler prototypes are used to save the time and expense of producing a complex and functional prototype since it may be quickly discarded (Nielsen, 1993, page 94), and the range of functionality of the prototypes often increases as the iterative cycles proceed.

The philosophy of user centred design is that many prototypes should be constructed, each the product of lessons learnt from the evaluation of its predecessor. Nielsen recommended a now common heuristic of just five users (Nielsen and Landauer, 1993). He based this on empirical evidence from eleven 1990s computer software projects where on average a single user found 31% of problems. He assumed that the software had a quantifiable number of problems, and that if each user found a proportion γ of them, then the proportion of the problems p found by N users testing one iteration would be:

$$p = 1 - (1 - \gamma)^N \tag{6.1}$$

His reason for proposing such a small number of users was efficient resource usage – it is better to test three iterations with five users each than one iteration with fifteen users, since although the proportion of problems found is the same the design benefits from more iterations. Hence, the calculation is reduced to the minimum number of users needed per iteration. However, this heuristic has recently attracted controversy, partly because of methodological considerations – γ needs to be between 0.30 and 0.4 to find about 85% of problems, and users need to have genuinely stochastic performance and total test coverage (Schmettow, 2012), but also because it does not take into account the severity of problems which remain undetected (Savoy et al., 2009). A further criticism is that the advice is frequently misunderstood as meaning that one iteration with five users is sufficient because testing only needs to discover 85% of issues, and the remaining 15% can be safely ignored (Schmettow, 2012).

Expert opinion can be used at any stage in the design cycle. A group setting is common, with between 4 and 6 experts and it is helpful if they fill in a questionnaire at the end of the session to summarise their findings. However, as good as expert assessments are, they are a poor substitute for user opinions and should not be seen as a replacement for them (Melchior et al., 1996b, page 45–50).

Heuristic evaluation is similar to expert opinions as it uses experts in the product or the target user group, or both – so-called "double experts" (Melchior et al., 1996b, page 49) to identify problems based on how well the product follows a checklist of general principles that codify the best practice for that type of product. It is recommended for both early design and in later prototype iterations (Nielsen, 1993).

It is normally done either by demonstrating the product to a panel or having individual experts attempting specific tasks with the product. It differs from expert opinion because the evaluation is simply for compliance against heuristics rather than a more open ended discussion (Melchior et al., 1996b, page 49).

There is a close relationship between guidelines and heuristics, the terms often being used interchangeably or heuristics being just an alternative representation of the same information in a form more appropriate for evaluations. There are specific sets of heuristics which have been developed, particularly for human computer interfaces where Nielsen's Ten Usability

Heuristics, based on an analysis of 249 usability problems encountered (Nielsen, 1994), is probably the most common. However, where there are no specific established guidelines for the device under consideration, heuristics must be specifically developed either empirically or from an overarching set of principles (Tsui et al., 2010).

Heuristic evaluation has been criticised as lacking breadth by focusing on highly circumscribed parts of the functionality, and in its purest form will often find only minor problems whilst ignoring the context in which the product is used (Cockton and Woolrych, 2002). it remains popular as an easy “discount” method (Nielsen, 1993) that can quickly identify usability problems without requiring real users or formally trained testers.

Performance measures (or metrics) are quantitative tests which provide numerical data for either comparing different products in an objective fashion or to test whether performance goals have been achieved. They are used both in design, for example Nielsen (1993) suggested them for competitive analysis and final testing in determining usability of computer interfaces, and for ensuring that the product meets the customer’s requirements (Ulrich and Eppinger, 2012, page 94). The choice of measures needs to be considered carefully to ensure proper coverage of user needs, particularly as represented in the product’s marketplace and so that they can be measured easily, with ideal and limiting target values (Ulrich and Eppinger, 2012). There are several standards which define usability metrics, almost exclusively for computer systems, such as ISO 9241-11:1998 and ISO 9241-304:2008 on user tests for computer display terminals and PD ISO/IEC TR 9126 providing guidance on software metrics.

User and field trials involve actual or prospective users testing the product. For limited early testing observing the user attempting to use the device is often informative, but eventually the product needs to be tested over an extended period. Activity diaries are commonly used, either to note use or problems.

With computerised products software can record definitive data about use by automatic logging and it is often helpful to provide a facility for the user to add their own comments to the log as they use the system (Kuniavsky, 2003).

User feedback should continue to happen after there is a product – once it has been manufactured and released to the market and is used to inform future versions.

6.2.7 USER*fit*

USER*fit* is a set of nine tools, shown in Table 6.2, which summarise the results of the design process. It is particularly attractive for the design of the fall detector because it is intended specifically for assistive technology.

The tools are template forms and accompanying instructions provided in the USER*fit* Handbook which forms the basis of the methodology (Melchior et al., 1996c).

These tools are used in the context of a four stage design process model. These stages are the Problem Definition, Functional Specification, Build and Test (Melchior et al., 1996a). Problem Definition is subdivided into understanding the problem that the product is to address in the environment in which it operates – Context of Use – and the characteristics of the users, the product and the tasks – Analysis.

This corresponds to the first two stages in the ISO 13407:1999 (ISO, 1999) model of understanding the context and defining the requirements. However, the later stages are much more restrictive than the ISO model since the building stage is the actual construction of a product without any evaluation or feedback from users as this is done in the fourth stage. However, these individual stages can be repeated iteratively (Melchior et al., 1996a) and the USER*fit* tools can be used in other process methodologies.

USER*fit* tools cover all of these stages with the exception of the Build stage since this is the design and construction of a prototype from a complete specification and does not require user input.

6.2.8 Recruitment

User centred design is impossible without access to a sufficient number of representative users. However, accessible design complicates recruitment because of the great diversity of functional abilities amongst the target population. For elderly people in particular, there are enormous variations in capabilities and functional impairments even within groups of the same age, as well as substantial differences in knowledge and skills (Newell et al., 2010; Gregor et al., 2002).

It is therefore difficult to define a representative set of characteristics for the small sample who are to be involved in the design. Some people have specialised requirements which are poorly understood, and the diversity also introduces the likelihood of conflicts in accommodating people with different impairments (Newell et al., 2010), for example the tactile paving used at road crossings to guide people with vision difficulties can cause problems for wheelchair users (Ormerod et al., 2014).

Poor mobility and deteriorating health can also make participant recruitment and retention hard, as well as making it difficult for them to attend workshops and other meetings. This can result in designers having to visit users individually which slows the design process. It may also increase the number of different stakeholders who need to be considered since the user is

Stage & Activity	Tool name	Description
Problem definition – Context of Use	Environmental context	Summary of the business case for the product – justification, likely purchasers and users, etc
	Product Environment	Summary of the support environment that the product will operate in, and the implications which this has for the design
Problem definition – Analysis	User analysis	Summarises the defining features of the likely users of the product and their characteristics
	Activity analysis	Captures the activities that the users of the product will engage in when using it and how this affects the design
	Product analysis	Collects the functional requirements of the product and transforms this as a list of features
Functional specification	Product attribute matrix	Maps the user attributes and activities onto the product features and requirements
	Requirements summary	Summary of requirements and how well they correspond to the user requirements
	Design summary	More detailed functional specification
Build	-	
Test	Usability Evaluation	Defining the evaluation criteria and testing the product against them

Table 6.2: The nine USER*fit* tools (Melchior et al., 1996c; Poulson and Richardson, 1998)

often not the purchaser, who might be a family member or even a local authority (Newell et al., 2010).

Involving people with even minor dementia is an issue since informed consent may be hard to obtain or maintain, and participants may have difficulty communicating their views (Orpwood, 2004). The inability to maintain attention and tiring easily can cause further difficulties, for example resulting in a casual rather than a rigorous evaluation of any prototypes.

6.2.9 Conclusion

This review has shown that user centred design is essential for successful assistive living products. The recruitment of representative users can be difficult because of their diversity and the difficulty which their functional impairments may bring to their input to the design process. This review demonstrated that there are many design techniques and tools to choose from. The choice is governed by the specifics of the product and the target audience, and the resources available to the designers.

6.3 The fall detector design study

This section describes the overall plan and first stage of the fall detector design study. This user centred study had the aim of determining the most acceptable physical format for a wrist-worn fall detector for people with dementia. Within the available timescale it was accepted that it would not be possible to produce a complete prototype system, but it would be possible to determine the key characteristics of the device.

6.3.1 The process model

The basic design process model used in this study was taken from ISO 13407:1999, described in Section 6.2.4. Although the standard has been superseded, the model itself is still valid:

- Stage 1 Understand the context in which the product sits
- Stage 2 Define the requirements for the product
- Stage 3 Produce the design solutions
- Stage 4 Evaluate the solutions

The study replaced the single user requirements document with the set of USER*fit* documents (Melchior et al., 1996a) described in Section 6.2.7. It was originally anticipated that two iterations of the last two stages would be needed – one to validate the basic design and identify unsatisfactory aspects and the second to validate their rework.

6.4 Context and requirements

The context in which the fall detector has to operate was developed from both existing qualitative literature and the understanding built up informally through a considerable amount of contact with people with dementia and their carers through frequent voluntary work with dementia support charities, family experience, discussion with medical professionals and from previous work with people with dementia and their carers at Designability.

Orpwood (2004) highlighted difficulties using people with dementia in the early stages of design studies, and suggested using carers with their understanding of the people they care for. Hence, a decision was made to use carers. Carer input was also important since they interact with the device themselves and make the decision about its purchase.

Focus groups were chosen to capture the requirements because of their efficiency and the wide range of views which they can quickly produce because of the opportunity for participants to interact with each other.

6.5 Recruitment

Ethical approval for the study was obtained from the Health and Psychology departmental ethics committees (see Section D.4). Two hundred and twenty eight carers were identified as suitable by BANES Carer's Centre and contacted either by letter (168) or email inviting them to take part. Flyers advertising the study were circulated at local Alzheimer Support meetings, local WI groups and a local Carer's Centre as well as publicising the activity through word of mouth. In addition, presentations were given at four Alzheimer Support meetings.

Potential participants who expressed an interest were contacted by email or telephone and thus a relationship was established with the investigator prior to the focus group. Three of the participants were previously known to the investigator. A total of 13 participants took part. The groups took place in two towns in South West England. The participants are summarised in Table 6.3. Some participants knew each other – Group 1 was recruited from one WI group, and a married couple attended group 2. Two participants cared for people several hours away, whilst the other non-resident carers lived much closer. One resident carer looked after her husband, and the other her mother. The professional carers were a former nurse who also cared for a relative, a former care home worker and a professional who provided support to carers. The experience of dementia severity varied from undiagnosed very mild dementia

Group	Location	Day	Professional carers	Non-resident carers	Resident carers
1	Participant's home	Weekday	1	3	0
2	Meeting room	Saturday	2	3	0
3	Meeting room	Weekday	0	2	2

Table 6.3: Focus group participants

or mild cognitive impairment through to severe dementia. The majority of dementias were Alzheimer's or related, with two carers caring for someone with frontal lobe dementia.

6.6 Method

The procedures for the focus group were initially tested and refined with the assistance of a university patient public involvement group.

The session commenced with a five minute presentation on fall detectors to ensure a common understanding amongst participants, which briefly covered the following points:

- Background on the incidence and outcomes of falls in elderly people.
- An example of a commercial wrist-worn fall detector and a simple explanation of the functioning and principles behind the device.
- The issues around producing a fall detector which can be worn by people with dementia and which would alert a resident carer in the event of a fall.
- The researcher's interest in the subject, the research goals and methods.
- The efficiency of commercial fall detectors, and the possible use of pulse measurements, which constrains the choices.
- That the fall detector need not look like any existing devices.

An illustrative selection of other objects worn on the wrist, Figure 6-2 was available for people to use in the discussion. The discussion then took place covering five different themes of the design, with fifteen minutes nominally allocated to each. The themes are shown in Table 6.4.

Figure 6-2: Other wrist worn objects shown in the focus group

The sessions were audio recorded to allow anonymised transcripts to be produced. Participants were not provided with copies of the transcripts to correct, but the transcripts were independently reviewed for veracity.

6.7 Transcription and analysis

This study investigated specific questions about fall detector design which were heavily constrained by technical possibilities and which demanded reasoned responses. Consequently, thematic analysis was used, with emphasis on semantic themes readily apparent from transcripts rather than looking under the surface to glean latent themes. Since most of the themes were pre-selected by the investigator to answer specific design questions, a theory-driven approach was appropriate.

Thematic analysis is widely used but is nevertheless controversial in parts of the qualitative research community where it is seen as too loosely defined. Braun and Clarke (2006) argued that it is often used where no technique is identified or even when formal methodologies are claimed.

Transcription always involves making representational and interpretational choices about the spoken data (Bucholtz, 2000), and is therefore part of the analysis process since the style of transcription selected depends upon the goals and analysis technique being used. It is important that transcription leaves out irrelevant detail which would otherwise make the transcript harder

1. What should the fall detector look like? What is the most likely thing that someone that they care, or cared for would wear on their wrist? What shouldn't it look like?
2. The strap The ethical and practical problems of having a device which cannot be easily removed by the wearer were explained, along with the drawbacks of having an easily removable device. - What should the clasp be like? - How easy or difficult should it be for the wearer to remove the device? - Should the strap break easily? - Should the device warn if it is removed?
3. Raising the alarm - How should the device raise the alarm to the carer when there has been a fall? - Should the wearer be informed that an alarm has been raised? If so how? - Should there be an audio link between the carer and the wearer? How important is that?
4. Physiological data The device will incorporate a pulse sensor. This could be used to alert the carer to distress or agitation or a small number of medical problems. This greatly decreases the battery life and might generate extra false alarms! - Should the device also sense distress or agitation physiologically, or sudden medical problems? - Should the carer be provided with more information than just the alarm? - Should the wearer be able to activate it manually? Does this affect the appearance?
5. Battery management Battery management is vital and affects everything. Explaining that largest contributor to the volume of the device would be the battery if the device was to have any extended battery life. Assume the battery only lasts two or three months. If the device is to detect distress and agitation then the pulse sensor will be active much more often which means that the battery may only last weeks or one month instead of, say, three months. A possible scheme was explained whereby replacement device was delivered to the carer, with the old one sent back to the suppler. - How should battery depletion be handled? Which would be better – replacement batteries, replacement devices, rechargeable device? Can you think of other ways of doing this? - From your experience is there anything else about the battery that we should consider?

Table 6.4: Themes for the requirements focus group

to follow (Ochs, 1979). For the research goal of understanding participants' opinions about fall detector design it was sufficient to undertake ordinary transcription using standard orthography with limited annotation, for example indicating objects that the speaker was talking about or gestures.

The transcripts were coded with the assistance of NVivo 10 for collation. The initial codes were derived from the questions the participants were asked, shown in Table 6.4, and developed into a larger hierarchy. New codes were identified when they arose in more than one focus group, more than one participant engaged with and discussed them, or because they were novel. The process was selective since discussion which was irrelevant to fall detector design was not coded. The codes were then reviewed to find additional relevant themes across the dataset which were outside of the questions asked.

6.8 Results

There was an overarching theme that familiarity and habit are extremely important in Alzheimer's and related dementias and participants stressed this time and again. In addition, several participants said that the people that they cared for were unconcerned about falling.

The discussions also frequently touched upon the gradual deterioration of the person and that whilst changes to the individual's environment could be made early on in dementia it became increasingly hard, as well as becoming much more distressing for the sufferer, for example:

> "I think sometimes the issue is if someone starts wearing something before they are too bad on dementia."
>
> (Participant A1 (i.e. participant A in the first group))

There was a desire to personalise the device to the carer's and the wearer's life, for example enabling or disabling different features as required such as the ability to detect distress or anxiety. Although there were only two resident carers in the study, their views, and requirements, were not substantially different from those of non-resident carers.

6.8.1 What should the fall detector look like?

A vital consideration for the participants was that it should look familiar. Anything strange was likely to worry the wearer or cause the wearer to remove it. Participants in two groups expressed concern that an unfamiliar device like a fall detector would be unsuitable in many cases:

> "Even if I could get it through to her what it was and why she was wearing it she would still worry that it wasn't working or that she'd got to do something to it . . . . It would just bother her." (Participant D1)

> "But with my father would be quite suspicious of things he doesn't recognise. He'd think it might be some recording, something being recorded, and pretty suspicious." (Participant D3)

Where people were already wearing personal emergency response alarms or other devices, it was in several cases a struggle for the carer to ensure that the individual wore the device. One participant cared for someone who wears a wrist worn pendant alarm and commented that he frequently discards it. Another commented:

> "It's only when you go in and he [participant's husband] says "oh you haven't got this on" that he [participant's father] says "Oh yeah", "put it on" but he does take it off." (Participant B2)

The strong consensus in all three groups was that the fall detector should look like a watch since this was an object that everyone would recognise, accept and many would be used to wearing.

> "I think honestly something that looks like a watch would be the most normal thing for most people to accept that that is what it is." (Participant A1)

One participant pointed out that it would nevertheless be difficult to persuade people who did not habitually wear watches to do so. Another mentioned that a watch-like device would also help reduce the stigma of having an assisted living aid. A different focus group suggested that since many elderly people feel the cold easily, watches were often hidden underneath long sleeves.

Some other alternatives were proposed. Making it in the form of something to do with clothing was discussed – cuff links or buttons – since everyone wears clothing, but the group noted that changing clothes would present a problem. Similarly, glasses or hearing aids were suggested but the impracticality of this because of their removal at night was seen as a disadvantage. Belts and chains were also briefly discussed, along with their practical problems. A device worn around the neck was mentioned by one participant because her mother removed watches and rings when preparing food.

There was also discussion about devices fitted to the ankle in two of the groups because of the difficulty in getting to it, although again the lack of familiarity would cause distress. However, one of the participants, originally from Pakistan, suggested that the ankle would be well suited for cultural groups where anklets were common.

There was limited discussion about the size of the watch, and about the type of watch face, but no firm opinions or conclusions, although several participants pointed to the gender-specific differences in watch design.

> "What they're used to, isn't it - what they're used to. You know, we all look at the time and say well it's ten to three. But the digital one, well you're thinking well OK." (Participant B2)

One suggestion was to use a smart watch type display to build a device which could stimulate memories, for example by showing photographs of grandchildren, but other participants warned that as the dementia progressed the wearer may forget who the people were – a participant said that her husband no longer recognised photographs of his grandsons.

This could also provide information such as telling the wearer whether they had eaten, or showing them pictures as reminders of what they should be doing – for example bed or mealtimes. The professional carer support worker suggested that it might also function as a dementia clock indicating time of day. Whilst a smart watch offers many possibilities, other participants were concerned that it may have more limited use.

> "Yes, because my husband doesn't recognise photographs of his grandsons. He sort of knows he should know them, but unless someone pointed out he wouldn't realise they were personally. . . " (Participant B3)

Members of the groups had strong reservations about the practicality of replacing the person's existing watch where they had more advanced dementia, as illustrated by the following exchange:

> "Quite a lot of emotions, it's memories. It's all of those things. It's given by my father and all that sort of stuff. The logic of replacing it with something that tells the time is irrelevant really. It's just not my watch. I've not tested it, but I suspect that would be the case." (Participant A3)

> "[Participant's husband] would be the same. It's his watch. He doesn't remember when he had it but he is so used to seeing it there and he, if someone had given it yesterday he wouldn't recognise it. But because it has been there for such a long time then it's comfort." (Participant B3)

Several participants commented that people continue to wear their watches through habit even when they we no longer able to tell the time. One suggested:

> "If that was your favourite watch you've been wearing for years, you probably wouldn't want to wear something else. Have you considered something that will adapt to fit on the back of a watch? And that would be in contact with the skin. But again it's, it's ensuring that it stays on." (Participant C2)

The idea of a device which fitted to the back of the watch was raised within the third group following a suggestion by a participant that the device might be incorporated into her mother's watch, and that group saw it as something which would be practical, with one participant commenting on its potential flexibility.

> "So you could actually choose something that the person would want to wear that they like and then the device could get put onto it." (Participant C3)

6.8.2 The strap

There were mixed views about how hard it should be to remove the strap, with one group considering how difficult the device should be to remove, whilst the other two groups taking it for granted that the wearer would be happy to wear a watch and considering how to make the device easy to remove.

Although a participant in the first group initially stated that she would make the device impossible for the wearer to remove despite the possible distress her mother would have felt, the group concluded that the device should be fiddly or slightly awkward for the wearer to remove, but not impossible.

> "But I think you could make it so it was not impossible to take off, but awkward to take off." (Participant D1)

The other groups suggested that the strap should look normal, and spring straps, expanding straps, and the design of buckles were all touched upon. Spring straps, expanding or elasticated straps were favoured because they were less likely to come off entirely although one participant warned that spring straps catch in the hairs on arms. Clasps and buckles were discussed but concerns were raised about clasps as hard for people with arthritis.

Although the fall detector shown to the groups used Velcro, two participants thought that it would be unsuitable because of the tendency to catch on fabrics and the distress which might be caused by the noise.

> "Also that noise is someone who, who's a bit jittery – it's quite scary – those Velcro noises." (Participant C3)

The question of whether it should generate an alarm if removed was discussed, and the consensus was that it should, either immediately or after ten minutes, for example if not replaced after washing. A delay of ten minutes might, at the expense of false alarms, be taken as an indication that a fall *may* have occurred because the individual may have not been able to put the device back on, and so action triggering a check on the wearer would be recommended.

> “If they are happy with the watch and they will wear it, the one thing you probably want to know is if they have taken it off and then it can send a little warning to you.” (Participant C2)

Some participants discussed when watches were worn – some took their watches off at night, or when they showered and two participants talked about removing watches and jewellery when preparing food. Several people said that it would be difficult for individuals to change their habits, and a person used to often removing their watch would continue to do so, although in the third focus group two participants commented that whilst the people that they cared for had routinely removed their watches they had stopped doing so as their condition worsened.

6.8.3 Raising the alarm

The choice presented was straightforward – either informing a call centre which can then either speak with the wearer if this is possible or call a carer, or contact the carer directly. The outcomes of this discussion were varied. The first group felt that the call centre was the best route since their experiences had been good, with the conversation finally summarised as:

> “Call centre is tried and tested so go with that.” (Participant A1)

Opinions in the other groups were more diverse, and choices arose because just alerting a call centre was not as straightforward as it might seem, for example:

> “But if you are only in the next room and you haven’t heard it and it goes to the call centre – then you are not informed. I would think both.” (Participant D3)

There was some discussion about whether the behaviour should be configurable, so that when the carer was available the alarm would be routed directly to them, but it could be switched to the call centre if the carer expected to be unavailable for several hours. However, this presented problems, as one participant described to another who had suggested making it switchable:

> “That’s feasible as well but then you know it’s educating the carer to remember every time they go out as well that’s something else that has to happen isn’t it, because at the end of the day you – how far do you allow for human error whereas if something is in place that will happen it is functionable *[sic]* and it will happen.” (Participant B2)

Other choices included having the call centre as a backstop in case the call was not acknowledged although one participant thought that this might cause confusion, or even if the alarm routing behaviour could determined by the fall severity. One participant asked whether the alarm could detect consciousness, as this might be useful in determining how serious the situation was.

An alarm button on the device was considered pointless for people with advanced dementia, since the general view was that the purpose of the button would either not be understood, or if it was too easy to press then it would be done so by accident.

However, views were much more mixed for early dementia. Some participants though that the watch should have an alarm, especially for emergencies other than a fall – getting stuck in the toilet was given as an example. Others disagreed because people would not use the button, forget about it or because there was insufficient time to use it during a fall (and presumably afterwards). Some others did not think it should have manual activation either because wearers would not remember that they have it, or because the device was intended to be automatic.

One person suggested that it should be worn in conjunction with an existing panic alarm and another that the fall detector could be built into the back of the alarm.

6.8.3.1 Communication with wearer

Participants felt that voice communication would be practical in some, but not all, cases. The voice needed to be familiar and the communication channel opened automatically. The conventional method used in assisted living devices is to call the base station, but during the discussion one of the participants in Group 3 pointed out the difficulty with this if the person falls in a different room to the base station. Some participants in that group also raised the problem with people who had difficulty hearing. Two-way communication was to be preferred.

> "My mum's did the same, but it was this disembodied voice in the hall and mum had no idea who it was – She thought it was my dad come back for her. Which was rather sad." (Participant D1)

It was not be appropriate in all cases, since:

> "A talking watch would freak someone out." (Participant B3)

Although one group felt that even if the person didn't really understand what is going on, if they had fallen and were in pain it was still useful for them to be told that help is on the way.

> "For me I would prefer it to tell that person that yes some help is coming – a reassurance for them that, because if they are in a house on their own they're obviously frightened and they don't know, they might not be really aware where they are, . . . " (Participant B2)

During discussions of the communication range of the device, it was explained to the group that a long range device would use the terrestrial mobile telephone network, and several participants made two points. The first was that it was not clear if the person had left the house and returned whilst the carer was away, and that an alarm if the device goes out of range of the base station might be useful. A participant caring for someone with frontal lobe dementia mentioned an incident where she noticed a bruise on the person's head, and on inquiring found that he had tried to cycle to his dentists. The second point was that mobile phone coverage is sometimes patchy, and so a mobile phone connection around the house, where the device would almost always be used, would be inadequate.

6.8.3.2 Physiological data and monitoring

Most participants wanted to know if the person had become distressed, but one thought it would be better to wait a period – half an hour was suggested – since if it was only transient – the suggestion was if the wearer had seen a spider – then there was no need to alert the carer. However, concern was raised that the person's agitation might cause the carer stress, especially if they could do nothing about it, and that perhaps the carer could choose to disable it.

> "I think easier because I'd want to know frankly what is going on with my dad and sort of be able to monitor his condition and his, and, but then if it was affecting me to such a degree then perhaps somebody else could be doing the monitoring not me." (Participant D3)

6.8.4 Battery management

Participants were in agreement with replacing the device at regular intervals, but stated that they needed a reminder of when it was time to change the device or a way of monitoring battery condition.

Several people questioned how hard it would be to change the battery, and drew an analogy with hearing aids. One participant pointed out that replaceable devices would be harder to supply than replaceable batteries in developing countries.

Until recently, some models of hearing aid needed to be taken to a hospital department or other maintainer for battery replacement, but more modern ones have batteries which are regularly changed by the user or their carer and the two week life between battery changes was felt acceptable.

> "Well, you do it with hearing aid batteries, hearing aid batteries are prescribed so once I've run out I go to the GP surgery and say "can I have some more batteries", and they give me more batteries, and that works and so if that was a similar thing for me it wouldn't add anything more – it's the same, it's the same idea."
>
> (Participant A3)

6.9 Limitations

The principal limitation was the small number of participants which meant the study was only capable of obtaining a small range of opinions. The study focused on only one part of a fall detection system, and made assumptions about the physical characteristics of the device which constrained the range of views.

6.10 Discussion

The groups considered a watch superior to anything else for a wrist-based solution.

Whilst incorporating the device into a watch is an obvious suggestion, and some assisted living products do this, the idea that the people with more advanced dementia would be unwilling to wear a new watch was important. There are two different products to be considered.

For wrist worn devices, in the early stages of dementia a new watch could be provided which incorporated the fall detector, and this would continue to serve the person as the dementia progressed. The watch may provide additional information if the face was implemented as a smart watch.

For the later stages of dementia *their existing* watch could be retained, but now incorporate a fall detector. The most straightforward way of doing this would be to attach a small device to the underside of the watch. This requires a very compact fall detector since it must not change the feeling of wearing the watch.

Participants suggested the neck and the ankle as possible other sites for the fall detector. The neck would have some benefits as it could allow the heart rate to be measured more accurately using ECG (Gil et al., 2010). However, there are practical problems with a fall detector on the ankle, for example it would be necessary to instrument both ankles (Aziz and Robinovitch, 2011). Nevertheless, some authors have investigated fall detectors integrated into shoes or socks (Sim et al., 2011; Doukas and Maglogiannis, 2011).

These results from carers were broadly in line with the findings of Mahoney and Mahoney (2010), who interviewed 9 people with Alzheimer's disease and found that they preferred jewellery or wrist or ankle bands, and the review by Bergmann and McGregor (2011) which found that small, non-invasive devices incorporated into clothing or existing accessories were preferable to discrete devices. Some manufacturers of personal tracking devices for people with dementia have also tried to make their devices concealed, or at least discrete, for example incorporating it into the insole of the shoe (GTX Corporation, 2014).

6.10.1 The watch

A fall detector built into a watch is a practical proposition for some people in the earlier stages of dementia. It might also be acceptable to those people who were, as several participants reported, unconcerned about falling since it would be doing something useful other than fall detection.

They would habitually continue to wear the watch as they deteriorate and hence it could have features which are also appropriate for the worse stages of the illness.

6.10.2 The underwatch fall detector

A replacement watch is much less appropriate for the later stages of dementia, but modification of their existing watch by attaching a fall detector to the underside may be.

6.10.3 Raising the alarm

There was a range of views about where the alarm should be directed in the first instance but all participants believed that a call centre was essential, for example if the carer does not respond. One compromise would be to make it possible to change the behaviour so that alarms were directed in the first instance to the carer, with the call centre picking up the call if it was not answered within three minutes. However, this might be too difficult, for example identifying when the call has been routed to an answerphone instead of the carer. Hence, the safest design would be to always route the alarm to a call centre who can then telephone the carer.

Bidirectional communication with the call centre, or the carer, would be useful for some people. Whilst this is technically possible in a smart watch design, it may not practical since the tiny speaker might adversely affect sound quality and loudness. However, the watch might communicate with a room audio induction loop, as are sometimes installed for listening to television or radio. The even more limited space available in the underwatch device would make bidirectional communication difficult, and perhaps the greater degree of dementia of the wearers would make it more confusing.

An alarm button is similarly feasible in a fall detector watch, although a study of this type could not determine whether it would be a desirable or stigmatising feature for the majority of prospective wearers. Stigma might be reduced by concealing the button, but this might make it difficult to activate.

In the group which discussed the range of the device, there was no strong opinion that the range should be further than enough for the house and garden, 150 metres or so. The base station should issue an alert if it loses contact with the device.

6.10.4 Monitoring

The device should be able to detect removal, although not raise the alarm for several minutes in case it is temporary. It should also be able to infer consciousness from a lack of movement. Providing other information about the severity of fall was suggested by one participant, but it may not be feasible to draw reliable conclusions about this even from physiological data. Participants wanted to be alerted if the wearer became distressed, although in some cases where the distress lasted for several minutes to reduce false alarms.

6.10.5 Battery management

Battery management was easily understood by the participants, since most had experience of the limited battery life in smart phones and hearing aids.

The view taken during the planning of the study was that the battery life of several months in some existing fall detectors was problematic since Holliday (2012) found that care professionals considered a fall detector battery life of 3 or 6 months inconvenient. Most fall detectors have a battery life of between 6 months and two years. However, with near continuous pulse measurement the battery might last less than a month and it was assumed that this would be a serious limitation. Hence, schemes were considered, for example making them replaceable devices with the carer either provided with a stock of them or supplied with a replacement unit at regular intervals.

However, participants considered changing the battery every two weeks reasonable. Replacing batteries instead of the device is both cheaper and preferred from a technical standpoint since the new device would have to be activated and the old one deactivated which would be additional possibly complex tasks for the carer. The repudiation of the original assumption is therefore of considerable benefit, even if it does introduce implicit requirements to provide battery status to the carer and to verify that the device is working following battery replacement.

6.10.6 Smart watches

One of the proposals, for the earlier stages of dementia, was to build the fall detector into a watch. During the discussions one participant suggested that the watch could display other things apart from the time, for example photographs. In the discussion which followed suggestions about showing meal times or other information was proposed.

Rather than producing a specialist falls detector watch it may be cheaper and less stigmatising to adapt an existing device, and smart watches or fitness bands are candidates. A fall detector retails for around 150 pounds, roughly the same cost as a fitness band and about half that of a mid-level smart watch. Manufacturers of fall detectors are starting to add features such as activity monitoring and detecting stumbles (Tynetec, 2012), whilst sleep monitoring fitness bands are commercially available – altered sleep patterns is a common problem in dementia (Wang et al., 2010).

The market in smart watches is growing with 720,000 Android Wear devices sold in 2014 (Canalys, 2015), following on the heels of wrist worn fitness monitoring devices. Some watches, and fitness bands, use photoplethysmography to measure the pulse rate at the wrist, an innovation introduced in the Omron HR-500U launched in late 2012. These include the Fitbit Surge, LG G Watch R, and experimental devices such as the Multisensory Wristwatch System reported by Stankevicius and Marozas (2014), whilst one, the Jawbone, uses impedance plethysmography. Measuring pulse rate is a matter of looking for peaks in the waveform, a much easier task than accurately measuring pulse shape.

The devices may not be capable of measuring instantaneous PPG signal amplitude or even instantaneous heart rate because of a lack of perceived demand for these features. The Android Wear API, for example, only provides for basic pulse rate, and not pulse rate variability, with the API allowing the application to suggest a rate in terms of "fastest" rate, or "normal" rate, which the wearable device may ignore. However, one non-Android manufacturer has announced a model which has an open expansion path for both hardware and software, in this case a strap which can be replaced with one carrying extra sensors (Orlowski, 2015).

Smart watches have large high quality displays, and apps can be added as the dementia worsens to help with assistive living tasks. They normally use Bluetooth networking, which suffers from a short range, although Android Wear 5.1 also supports WiFi, and Android can easily be run on servers as well as tablet devices and so the server end of the connection is not restricted to a mobile phone. However, the main drawback of smart watches is the short battery life, usually only two or three days at best.

There is an overlap between smart watches and other fitness bands, of which 4 million were sold in 2014 (Canalys, 2015). Whilst the longer battery life – of a week or so – is beneficial this is offset by the much poorer display. They are rarely programmable devices in the way that smart watches are, but many can communicate with a smart phone which could run a fall detection algorithm although the communication distances are typically only a few metres. However, fitness bands are largely only attractive to people with an interest in fitness which may limit their market penetration to a wider community.

6.11 Conclusion

Much of the contextual information provided by the carers is well documented. It was no surprise that falls are a major concern for many (Walker et al., 2006; Lach and Chang, 2007), or that familiarity is critical in design for people with dementia (Boger, 2010). The value of this study from the perspective of the thesis was in the detailed information it provided about how to implement a wrist-worn device.

The focus on the wrist watch is an important outcome, since despite its declining popularity amongst younger people, it is a device which many older people with dementia use. Using a smart watch seems possible in the early stages of dementia as these devices offer the prospect of a wide range of useful assistive living applications will become available which use them. Several fall detection apps have been written for Android phones, and so it seems natural that this will be done with smart watches.

Something more discrete is needed for more severe dementia because of the difficulties in introducing a new device to the individual. The suggestion for the later stages of dementia was to provide a device which fitted underneath an existing watch. This is more novel than using a smart watch, and is explored further in the next chapter.

The next chapter takes the underwatch concept further by fleshing it out with a tentative technical design to understand the physical limitations. It then describes a small study to evaluate the concept using non-functional prototypes with carers, to understand whether it really is an acceptable approach and determine the physical limits needed for the device.

Chapter 7

The underwatch fall detector concept

The outcome of the focus groups described in the previous chapter was to implement the fall detector as a watch in one form or another. For later stages of dementia, the idea of a small fall detector fitted underneath an existing watch and out of the wearer's normal visual field is an interesting and novel proposition.

This chapter explores this concept further, by considering some of the technical design issues and describing a series of interviews with carers at which inert prototypes were demonstrated, to further assess and refine the concept.

The underwatch device would use an accelerometer and perhaps other kinematic sensors, supported by physiological sensors. Whilst the main function of the physiological data would be to provide confirmation of a fall, informal discussions with clinicians showed an interest in obtaining information about the cause of any fall. The NICE guidelines (Centre for Clinical Practice, 2013) recommend a multi-factorial falls risk assessment following a fall and the fall detector may have a role in providing information such as pulse rate at the time of the fall.

The conceptual design of the device is shown in Figure 7-1. The estimated thickness is about 5 mm, as shown in Table 7.1. The device is glued to the back of the watch, perhaps with a spacer to enlarge it to the watch diameter. It is powered by a coin cell, such as a CR2012, mounted within the device immediately underneath the watch since the skin side is needed for the pulse sensor. The pulse sensor and other electronics is mounted on a 0.8 mm thick printed circuit board. Six layer boards of this type are commercially available, although the radio frequency components may need to be carefully laid out. If one side of the board is utilised for the thicker 0.5 mm to 1 mm components, and the other for thinner components, 0.5 mm or less, this will add 1.5 mm.

However, to be able to understand the physical limitations of the device so that a meaningful evaluation could be carried out by carers, it was necessary to develop the design further.

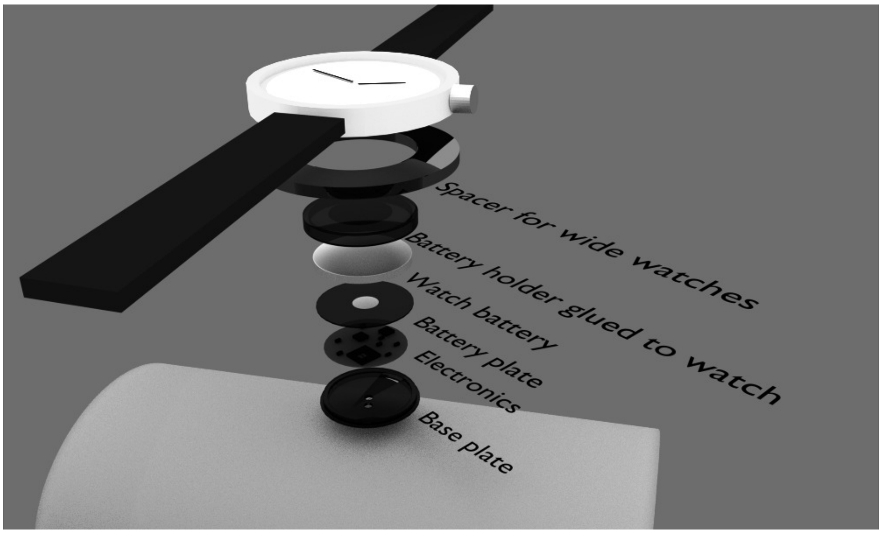


Figure 7-1: Conceptual design of the underwatch fall detector

Component	Thickness
Glue layer	0.1 mm
Case wall	0.5 mm
Battery	1.2 mm
Battery plate	0.5 mm
Electronic components	1 mm
Printed circuit board	0.8 mm
Electronic components	0.5 mm
Case wall	0.5 mm
Total	5.1 mm

Table 7.1: Estimated thicknesses in original underwatch fall detector concept

The design is necessarily speculative but allowed an informed estimate of the device's minimum size device to be made, particularly since reservoir capacitors and batteries can occupy a significant proportion of the volume of small low-power devices.

7.1 Design considerations

The device's diameter has to be small enough to fit underneath the wrist watch, and it must be as thin as possible. Most watches are roughly square or round, men's having a diameter in the range 34 mm to 50 mm and ladies' 22 mm to 44 mm, with most 42 mm to 45 mm and 35 mm to 38 mm respectively (SaySales, 2015). Case thickness varies from 6 mm to 18 mm, with 8 mm to 12 mm considered the average (Payin3, 2015). There has been a trend towards larger watches over the past decade but even older watches could accommodate an approximately

25 mm diameter device.

A conceptual electronics design is shown in Figure 7-2, and more detailed discussion of some of the issues raised is included in Appendix C. It consists of four electronic subsystems:

- Microcontroller with integrated radio communications.
- Accelerometer capable of waking the microcontroller from a sleep state when acceleration exceeds a threshold.
- Pulse sensor for the pulse rate and pulse shape measurements. The LED is turned on for extremely short periods during actual pulse measurement to minimise power consumption.
- Power supply and management. The LED and radio link are high power components which operate in bursts powered by a reservoir capacitor drip charged from the coin cell.

7.1.1 Microcontroller and communications

The microcontroller and communications subsystem controls the device and provides the communications with the base station. It would use either a chip antenna just inside the sidewall or a wire antenna wrapped around the outside of the device.

The device communicates using a very low power digital radio technology, either Bluetooth Low Energy (BLE) or ANT. Whilst both are capable of ranges of 50 metres or more this is unlikely to be achievable because of the small antenna size and shielding by the watch and the wearer, and the low output power of 5 dBm or less.

If 10 metres range can be achieved reliably, it may be extended using a self-configuring repeater scatternet around the home, 10 metres or so apart. The repeaters would route messages between the underwatch device and the base station. ANT may be preferable to BLE, since whilst both can form scatternets, BLE lacks a standardised procedure for doing so and distinguishes between master and slave devices in each piconet. The repeaters would be battery powered – an alkaline AA 2.7 A h battery normally operating at 27 mA for one second every fifteen minutes, and 10 µA for the rest of the time would discharge at 0.03 mA per hour and last about a decade.

The wearable device could either send just alarm notifications or more substantial data to the base station. Alarm notifications would be preferable to limit the high RF system power consumption, but it is assumed that the computational load would require data processing to be offloaded onto the base station. After a possible fall the device would monitor kinematic data,

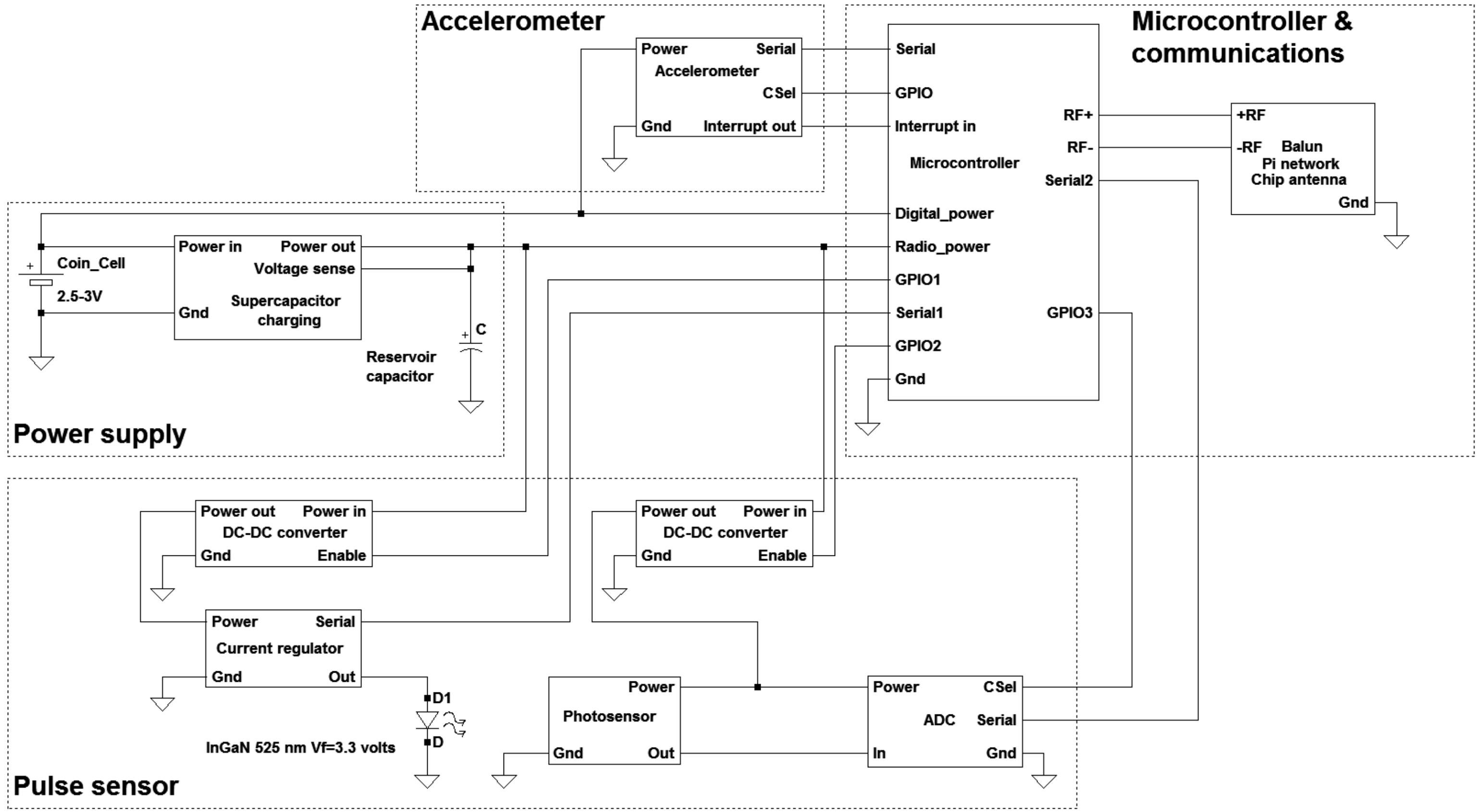


Figure 7-2: Fall detector electronics system block diagram

and read physiological data for 20 seconds or so, possibly after a delay to allow physiological responses to complete, transmitting a compressed summary to the base station for further processing. The energy needed for radio communication is relatively large, since it consumes 20 mA to 30 mA continuously during transmission and the reliable data rate is only 20 kbps. Hence, it is critical to minimise the amount of data transmitted.

7.1.2 Pulse sensor

The pulse shape sensor uses a significant amount of power. If the device were to simply measure pulse rate then a relatively low powered LED is sufficient because the amplitude resolution requirements are less stringent.

The strategy to minimise power is to make very short measurements of reflected light level. The pulse shape studies used a high pass analogue filter to remove most of the quasi-DC component, which is difficult in a very low power underwatch device because the filter settling time was longer than the interval between samples, so the LED and photosensor would have to be powered continuously during measurements. Pulsing the sensor and LED on for very short periods during which it is sampled by a sample-and-hold circuit would be more efficient. However, the sampling capacitor would need to store a relatively large amount of charge on each sample since leakage over a fraction of a second would be important at the resolution required, and the analogue filter continuously powered.

The remaining alternatives require a higher resolution ADC than the ten bit device typically built into microcontrollers, and using a digital filter to remove the quasi-DC component. A digital filter is designed to work on discrete samples, and a further benefit might be a substantial reduction in the digital filter's settling time by preloading it with estimates of the settled output.

A prototype infrared pulse sensor incorporating a high resolution 20 bit ADC and no hardware high pass filter was constructed during work on improving the pulse sensors in the previous studies. This provided a resolution of 1 ppm, corresponding to 5 μV at 5 V. Whilst its electro-optics were abandoned as unsuitable for the wrist, the direct digital readout worked, as shown in Figure 7-3 for the fingertip.

The pulse shape work used a 515 nm InGaN LED with a 3.3 V forward voltage. This is higher than the maximum battery voltage, and a single cell supercapacitor's 2.7 V limit, so a boost regulator or charge pump is needed. This must be supplied by the reservoir capacitor because at its maximum brightness the LED drew roughly 4 mA, far more than the battery can provide, and the voltage step up will require even more current on the input side.

A lower forward voltage diode would be preferable to eliminate the need for a voltage step up. The wavelength must be in the 500 nm to 600 nm range which shows the greatest pulsatile

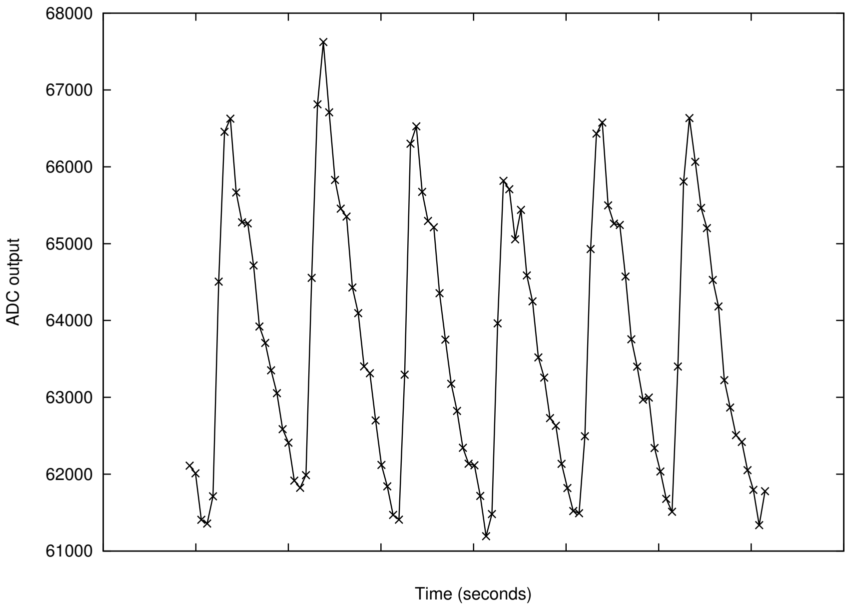


Figure 7-3: Directly digitised pulse shape from an infrared sensor at the fingertip. The signal is inverted because of the photo-transistor circuit used and digitised by a 20 bit analogue to digital converter.

modulation depth (Tamura et al., 2014). Whilst there are several LED other types in this range, none approach the efficiency of InGaN. The most efficient is the AlGaInP LED at 570 nm with a forward voltage of just 2.1 V, but it is only 30% of the efficiency of InGaN devices and would require correspondingly more power.

The LED brightness must be optimised to the wearer's physiology and the photosensor response. An adjustable current regulator is more energy efficient than current limiting resistances. Conventional LED drivers would be unsatisfactory since they generally control brightness by adjusting the duty cycle.

In the original conceptual model, the sensor portion of this subsystem also needed a voltage regulator, particularly if the voltage required was greater than 2.5 V.

The component ratio, the ratio between the pulsatile signal amplitude and the quasi-DC amplitude (see Section 3.1), seen in the pulse shape studies was estimated at around 1% although assuming a component ratio of closer to 0.3% may be safer. A resolution of about 3% is needed which suggests a resolution in the overall reflected light signal of about $0.3/100 \times 3/100 = 0.9/10000$, or one part in 11000.

The ADC would be separate from the light sensor because most digital readout light sensors are intended for ambient light measurements and eliminate the flicker by taking tens of milliseconds to carry out a reading. Commercial off the shelf optical proximity sensors can be used for pulse measurement, for example the 200 µW sensor described by Chandrasekar et al. (2012), but they normally operate in the infrared. Mains interference should be smaller than in the devices used in the pulse shape studies since the device is far more compact.

Ambient light must be excluded from the sensor since small variations may ruin pulse readings, and because of the possible aliasing effects of 100 Hz fluorescent tube flicker. If the photosensor is located in the centre of the underwatch disk, then light entering at the circumference will traverse 12 mm of skin. Kamshilin et al. (2015) estimated the penetration depth in their green light imaging experiments as between 0.4 mm and 0.9 mm, but even the worst case gives $0.37^{12mm/0.9mm} = 8\times10^{-20}$. The greater penetration depths of longer wavelengths, particularly infrared, are considerably more problematic, and the photosensor itself would have to be insensitive to them, perhaps by covering with a suitable optical filter.

7.1.3 Accelerometer

The accelerometer draws sufficiently low power that it can be powered directly from the coin cell. Many devices can operate in a low power mode until configurable acceleration thresholds are exceeded, when they generate an interrupt to wake the microcontroller and switch themselves to a higher powered mode for readout. This could be used to wake the system at the start of a possible fall, perhaps when near free-fall is detected, or for continuous monitoring, wake it when almost any movement is detected. When the start of a possible fall is seen the accelerometer will continue to be monitored to detect the subsequent impact and any post-fall movements.

7.1.4 Power supply

The energy content of a battery is linked to its physical dimensions which are constrained by the diameter of the watch on top of it. A large diameter battery is preferable to a thick one to limit device thickness. However, coin cells have very restricted capacity – for example CR2012 has a capacity of only 58 mA h and average power consumption must be limited to ensure it lasts at least two weeks.

Most coin cells of $\geq$ 2 cm diameter are only rated to provide 0.2 mA continuously and smaller ones half that. If more current is drawn the high equivalent series resistance, 10 Ω or more, causes internal ohmic heating which reduces battery life and further increases the internal resistance.

Whilst low power components such as the accelerometer and the microcontroller can be powered directly by the coin cell, it cannot deliver sufficient current for the higher power radio and pulse sensor. The conventional solution in very low power electronics is to power such devices from a reservoir supercapacitor which is rapidly discharged when they are active but slowly recharged again from the battery during the longer periods of quiescence.

Whilst high power consumption for short periods can be tolerated using this technique, the recharge time can become a significant problem once the capacitor has discharged. The high power components will then be unable to function until it has recharged sufficiently to power them.

A high capacity capacitor could store enough energy for several cycles before depletion, but the energy storage capacity would always be finite, and it would increase the physical size of the capacitor, which would affect the overall device size.

The thinnest supercapacitors available are single cell devices with an absolute maximum rating of 2.7 V. For example, a GA109F capacitor provides 160 mF in rectangular 18 mm $\times$ 18 mm by 1.1 mm thick package which will fit into a 26.9 mm diameter disk (CAP-XX Ltd, 2013), and since the work described in this chapter was completed the same manufacturer announced a new 0.6 mm thick 60 mF to 180 mF product line in a 19.5 mm $\times$ 20 mm package. In the longer term this may change since extremely high energy density carbon nanostructure based devices are under development (Li et al., 2012a).

A suitable charging circuit is needed to recharge the capacitor from the battery, ensuring that the capacitor is charged as quickly as possible within the limitations of the battery and, if an electrolytic capacitor were used, ensuring that the capacitor's low maximum voltage is never exceeded. However, whatever size capacitor is used multiple activations without a chance of it recharging will eventually deplete it and the detector functionality would be compromised.

7.1.5 Mechanical considerations

As the original concept of removing the electronics to access the battery was probably too fiddly for many people, the design was modified to use a removable battery drawer, as shown in Figure 7-4. Since this would also be fiddly to open, a tool would be needed, which would be built into the base station case. It would consist of a groove that the underwatch device, still attached to the watch, could be slid along with a protrusion which would pop open the drawer. The battery would only fit smoothly into the drawer in the correct polarity.

The original conceptual design had the electronics contained in a sealed unit. However, to eliminate the lower wall of the device the electronics could be encased in a resin block which would also form the lower surface. The larger diameter of the device allowed more area for the components, so they may only need to be fitted to one side which will also reduce the thickness. The only component which needs to be on the underside is the photosensor which must be as close to the skin as possible.

Figure 7-4: CAD model of a 3-D printed mock-up of the underwatch fall detector used to demonstrate the battery drawer. The upper face in this picture is the side that contains the pulse sensor, placed against the skin. The battery drawer is shown removed on the right hand side.

The LED would be mounted on the printed circuit board with the lens pointing downwards through a hole in it. A CR2412 battery is 24.5 mm in diameter, which implies a device of at least 26 mm. It has a capacity of 100 mA h, which would provide about three weeks operation at the maximum continuous rating of 0.2 mA, or alternatively allow the battery to be replaced well before the voltage falls to its minimum.

The device was estimated to be 4 mm thick. A 1.5 mm thick supercapacitor might be added at a cost of an extra 1 mm thickness by judiciously moving thicker components to the edge of the board to allow the supercapacitor to be placed over 0.5 mm thick components. Additional thicker components can be placed either side of the supercapacitor, as shown in Figure 7-5.

Component	**Thickness**
Glue layer	0.1 mm
Case wall	0.5 mm
Battery	1.2 mm
Battery drawer	0.5 mm
Electronic components encased in resin	1 mm
Printed circuit board	0.8 mm
Total	4.1 mm

Table 7.2: Estimated thicknesses of fall detector without large reservoir supercapacitor

The outcome of the work was an understanding of the likely physical dimensions and functional limitations of the underwatch fall detector which was used to inform the construction of prototypes for the evaluation.

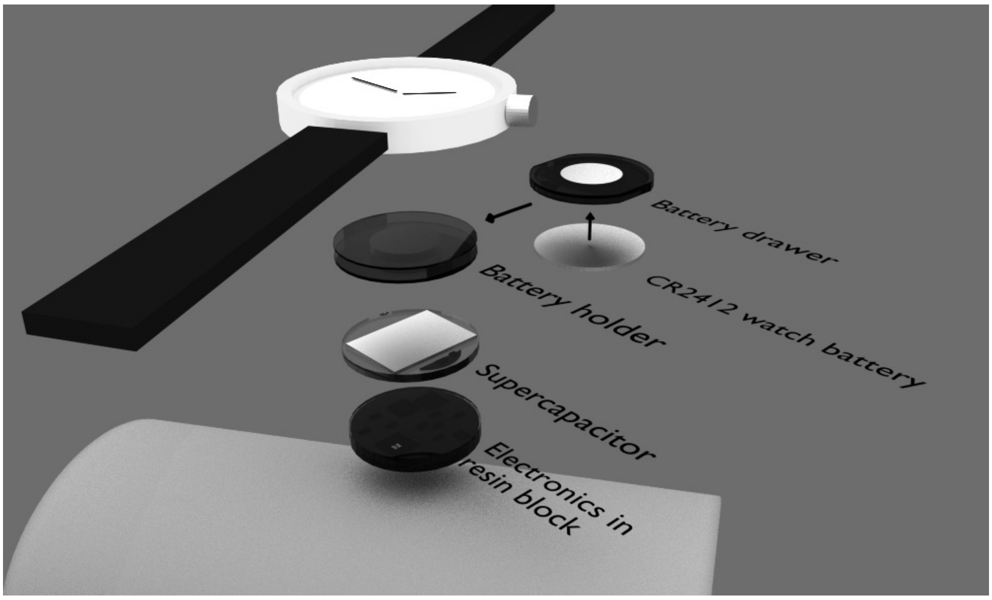


Figure 7-5: Underwatch fall detector with battery drawer

7.2 Evaluation

7.2.1 Method

The purpose of the evaluation was to assess how acceptable the reality of an underwatch device was to participants since the focus groups had discussed possible devices as abstract concepts. It took the form of semi-structured interviews of carers asking for their views on an outline design for an underwatch detector. This method was chosen since it would be effective in obtaining criticism of the overall concept, whilst not requiring the functional prototypes of user trials. They were preferred to focus groups because they would provide much more detailed criticism because of the amount of time spent individually with each participant. Ethical approval was obtained from the Health and Psychology departmental ethics committees (see Section D.5).

The sessions started with the author giving a summary of the focus group results and the developments made since then. He then gave an outline of the product and showed them the different features. The explanation was as follows:

- Smart watch for mild dementia. A picture of three smart watches with different displays was shown.
- The underwatch concept for more severe dementia,
  - The concept was explained, using Figures 7-1 and 7-5, and including an explana-

tion that it has an accelerometer and a pulse sensor

  - Models of the likely device sizes were shown. Several models were shown – three diameters and two thicknesses. It was explained that the model with the supercapacitor was the most likely but that the thinner one might be possible.

- The battery arrangement was explained using a 3-D printed model containing a battery drawer, and thin coin cells. The slot on the base station for opening the drawer was described.

- The base station and the possible need for a scatternet of repeaters was explained.

Several wrist watches were also provided as possible examples to stimulate discussion, and watch batteries to illustrate the type of battery which would be used. A photograph of the items used in the interviews is shown in Figure 7-6. The participants were then asked for demographic information about the people they cared for – ages, distance, relationship, whether there were other carers.

The interview questions, Table 7.3, focused on the acceptability of the underwatch concept, and in particular its physical characteristics. The two thicknesses chosen for these models, 4 mm thick and 5 mm thick reflected whether a large supercapacitor was required or not. Whilst the interview focused on the underwatch, some participants had comments about the smart watch too.

The interviews were audio recorded to allow anonymised transcripts to be produced. Participants were not provided with copies of the transcripts to correct, but the veracity was checked by another person. The transcripts were coded with the assistance of NVivo 10 for collation, with codes derived from the questions in the interview plan and new codes added as they appeared as common themes in a similar manner to the requirements study.

Analysis followed the broad pattern used in the requirements study, with thematic analysis following the themes discussed in the questioning, as described in Section 6.7.

7.3 Recruitment

Participants in the requirements study focus group who agreed to be contacted to participate in the evaluation were contacted by email. The interviews of those who responded were held in people's homes during the day or early evening of a weekday except in one case. In that case the interview was held during the day at an office located on the site of the local hospital. One participant was a spouse who had not been at the focus group, but was present at the interview and elected to take part. All participants were part-time carers of someone, elderly parent, or

1. What is your first impression of the device?
Likert scale: I hate it, I don’t like it, OK, I like it, I love it

Why?

2. What is your impression of the device
Thickness
Diameter
Shape
Colour
Anything else

3. How easy would it be to use?
Likert scale: Very difficult, Difficult, OK, Easy, Very easy

4. Would the wearer find it intrusive?

5. How could the device be improved?

6. What is your impression of the battery replacement?

7. How could the battery arrangement be improved?

8. Would you use the device?
Likert scale: Yes, No, Maybe
Why, or why not?
If “maybe”, what would make you use it?

9. Do you have any other comments about the device?

Table 7.3: Questions for the evaluation interviews

Participants	Care receiver	Distance	Live in carer	Dementia
A1	father	100 miles	wife	AD type
A2 B2	father	local	none	FTD
A3 B3	mother	local	husband	AD type
A4	husband	resident	herself	AD type

Table 7.4: Participants in underwatch evaluation interviews

parent in law, or had a spouse with dementia. One also worked as a part time carer in a care home. A summary of the participants is shown in Table 7.4.

7.4 Results

7.4.1 First impressions

All of the participants were very favourable to the device on first impression, either "liking" or "loving" it. The most critical of the participants raised a concern that the watch might catch on something, which was taken up by their spouse, and they suggested that a spacer or moulding be added to avoid a gap between the watch strap and the skin. The reasons given were that the device would be discrete – out of the wearer's normal vision range – and not having an additional item to wear. Some typical quotes were:

> "I think the idea is great, it really is because the watch is... My dad won't take it off. He loves to have it on. And then with time we could convince him of that. Reassurance and things." (Participant A1)

> "It won't upset his visual image of his watch so it shouldn't upset him. He might ask what's underneath but that, he'll accept that quickly I'm sure, yeah." (Participant A4)

However, it was noticeable that some participants changed their views about the device during the interview. It was initially seen as a device which was less intrusive to the wearer. As the interview progressed several participants became enthusiastic about the possibility that it might be completely concealed from the wearer. This may have been because of expectations raised during the interview with detailed discussion about the size, and in particular the thickness, of the device. For example:

> "I mean, yeah, this might be impractical because there are so many different brands of watches but you could take a watch and replace its back and say, right, the new watch back could be integrated, fitted on and then you haven't got something that can be easily removed." (Participant B2)

7.4.2 Physical characteristics of the device

7.4.2.1 Thickness

This was a major consideration for participants and whilst some participants found the 5 mm model acceptable several found it too thick and the 4 mm was preferred, although two participants felt that was only just so, as Table 7.5 shows.

Participant	Largest acceptable thickness	Comment by participant
A1	5 mm	“Absolutely fine”
A2	4 mm	“Right on the boundary”
B2	4 mm	“Right on the edge, or maybe a bit too much”
A3	5 mm	“I can’t see that being a problem”
B3	5 mm	“No problem”
A4	4 mm	“Much more acceptable”

Table 7.5: Participants views of the maximum thickness of the underwatch device based on the models they were shown.

Top row - models and batteries Left to right: 31 mm diameter × 5 mm. These models were made from circular cross section nylon rods, and painted very dark brown. 26 mm diameter × 5 mm. This was presented as the most likely size, with the other diameters for comparison. 20 mm diameter × 5 mm 26 mm diameter × 4 mm 26 mm diameter × 6.5 mm CR2032 20 mm diameter × 3.2 mm battery CR1616 16 mm diameter × 1.6 mm battery
Middle row - detailed model 3-D printed model of device demonstrating battery drawer (see Figure 7-4)
Bottom row - watches These included small ladies dress watches and a square watch

Figure 7-6: Objects used with evaluation interviews

7.4.2.2 Diameter and shape

The 2.6 cm diameter device was broadly acceptable to everyone, although some people worried that lady's watches would be too small, and the 3 cm diameter disk was considered too large by one person. Another participant noted that elderly people's watches tend to be large because of failing eyesight. There was a little discussion about having different sizes, perhaps with different battery capacities, but it was not seen as a critical issue.

The shape was not contentious – one person asked if square could be an option, but most people were happy for a round device.

7.4.2.3 Colour

One participant suggested that the colour be matched to the skin colour, and another was initially happy with the very dark brown paint used for the nylon models. However, other participants immediately stated that it should be silver or chrome to match the colour of the watch back, and those participants who initially suggested skin tone or the models' dark brown eventually concluded that this would be the best choice.

7.4.3 How easy would it be to use?

There was a positive response with most participants confident that it would be easy to use. The only differing view was the participant in the first session who linked this question to the thickness of the device and the degree to which her father would notice it. The participants in the other sessions were less concerned with concealing it completely but that the wearer would not have to do anything or even normally think or worry about it. No one identified problems for the carer once they had understood how to change the batteries.

7.4.4 Would the wearer find it intrusive?

Participants universally thought the device would not be intrusive, although some wanted it hidden completely from the wearer. In some cases the discussion turned to replacing the watch back with the device or even replacing the internal mechanism of the watch, and these were the only improvements suggested.

7.4.5 What is your impression of the battery replacement?

All participants thought the drawer containing the battery, with a tool for opening it built into the base station case, was a workable idea, and some remarked on the benefit of doing this rather than having a separate tool which would get lost. No participant could suggest a better battery arrangement, although some actively considered hinged lids.

> "Because like I said it would be a bit fiddly, wouldn't it, opening that. Even with normal batteries you find it quite difficult, but I think yours is the best idea. You know sliding it somewhere and unlocking. Unless that doesn't work or if things don't work it becomes quite annoying doesn't it, yes." (Participant A1)

One participant suggested dispensing with the battery altogether and using a pendulum in a manner similar to a self-winding watch.

7.4.6 Would you use the device?

All participants said would use it, or would recommend it. This should be qualified as they were asked at the end of the interview when they were engaged with the concept, although thickness influenced the decision. In addition Participant A1 gave a slightly ambiguous answer during a discussion about whether she would use it for her father if it was thicker. Nevertheless, the concept was favourable to all participants and suggests that it is worthwhile to develop further.

> "I think I'd think twice if it was thicker. But if it was incorporated it would be absolutely no problem, issues. And if it was thinner I would still consider. But I would think twice about a thicker thing. Not having to explain to my father would be, it's too sort of, too much effort." (Participant A1)

7.4.7 Do you have any other comments about the device?

There were no other comments, but the discussion did range to other areas. In particular the possible problems with radio range were explained along with the possibility of small self-configuring repeaters to route messages between the base station and the underwatch device. It was explained that these would be little bigger than the AA battery which powered them and would run for several years but would need to be distributed every 10 or 20 metres around the house and garden. No one objected outright to the repeaters but one participant raised a possible problem:

> "I can just imagine my mother, you know, going through her drawer - what's this, throw that out, you know." (Participant A3)

7.4.8 Smart watch

The smart watch concept for people with early dementia was not a formal part of the interview, but some participants commented as results of the requirements study were explained. It was an attractive idea to many participants, although two raised concerns about the complexity of smart watch displays and suggested that the device be configured purely as a watch, with a conventional time display.

7.5 Limitations

The study was very limited, with one set of fairly crude prototypes and a small number of participants. The outline design work was very basic and theoretical, and concentrated on the core functionality. The assumptions made for it, for example about battery power or RF range, may be incorrect which could have significant effects on the design of a functional device, as could additional features such as artefact removal strategies.

It relied exclusively on carers, even for the likely opinions of the people who would actually wear the devices.

Finally, the study only investigated one portion of a complex system, and aspects not investigated may have a serious impact. Its overall usability would be determined by many things, for example the usability of the base station's user interface and the efficiency of the device in detecting falls.

7.6 Discussion

The device was well received by participants. The most important criticisms were the need to make it as thin as possible and the risk of it catching on items if there was a gap between the strap and the skin. This latter point could be mitigated using some sort of spacer or former. The characteristics of the device from the interviews are listed in Table 7.6.

The study looked at a very small but critical component of a fall detection system. In particular, it did not cover the overall user experience, such as how the call centre would interact, how the device would be fitted, and the marketing decisions such as price. It only touched on the other physical components such as the base station and the repeaters, and only when a particular aspect of their operation was essential to the underwatch device itself.

It would have been premature to address these other areas, since the novelty of the underwatch concept revolves around the physical characteristics of the wearable device. These other aspects would be covered during subsequent design work.

Theme	Summary
Concept	Good. Need to decide whether goal is to hide from wearer completely or just be more discrete
Thickness	4 mm OK or marginal 5 mm too thick Ideally thinner
Diameter	2.6 cm diameter - OK
Colour	Same colour as watch back - silver/gold
Battery arrangements	Good
Repeater arrangements	OK. Might be hard to prevent wearer from throwing them away

Table 7.6: Summary of key findings from the interviews

The USER*fit* methodology proved very useful at the start of the study to provide a clear direction and structure. However, it became redundant as time progressed because the study was working with a small set of overall requirements.

Two evaluation iterations had been anticipated, but the evaluation study demonstrated that the concept was acceptable without major changes provided that the device is sufficiently thin. A key issue for this is whether a large reservoir capacitor is needed. Building a functioning prototype underwatch device was not in the study timescale, but estimates were made of the power consumption using the tentative electronic design described in Appendix C. This suggests that a reservoir capacitor is needed of only about 1 mF per 100 bytes of data transmitted by the radio link, although the coin cell limits the pulse sensor operation considerably. The capacitance might be feasibly reduced by having the device transmit data in several short bursts with the capacitor recharged in between.

This chapter demonstrated that the underwatch concept for people with dementia is a promising one, at least within the constraints of the small sample used for the evaluation. It also shows that it would be possible to build an accelerometer-based device which also made physiological measurements. In this way it presents a route for implementing a practical fall detector for people with dementia.

Steps following this are to further examine the concept, with representative user tests involving wearing the inert fall detector, and to evaluate a more complete system including other system components.

Chapter 8

General discussion and conclusion

This chapter provides an outline of the work described in this thesis, highlighting the main conclusions of each study and relating them to existing knowledge. It then looks forward to opportunities for further research which build on the contributions of this thesis.

8.1 Research aims

The goal of this thesis was to understand how a fall detector could be constructed for people with moderate or severe dementia. This is a large and complex question, but a very important one because elderly people with dementia are at much greater risk of falls than other people of the same age (Eriksson et al., 2008) and yet there are no devices specifically tailored for them.

The size of the question necessitated certain decisions to limit the scope. These were to restrict the thesis to the most common forms of late onset dementia because these affect the majority of sufferers, and to focus on wearable devices. These devices are far more widely used than fixed systems installed into the fabric of the building. They also suited the philosophy of the PhD to examine practical and inexpensive devices available to everyone in their own homes rather than adopt a more theoretical approach, even if this limited the scope of the research.

8.2 Approach

The work described in this thesis started with an examination of dementia and the issues around it. This did not just involve the literature review, Chapter 1, but also lengthy discussions with professionals and carers, and practical understanding gained from working and volunteering alongside people with dementia. It was important to properly understand both dementia and falling, to ensure that the technical aspects of fall detection were not considered in isolation from the wider context. For example, many technical papers expound effective fall detection strategies using sensors at multiple body sites, but leave unanswered the questions about how they could be implemented as practical devices.

This review yielded a clear understanding that many of the problems that people with the most common types of dementia face are due to episodic memory impairment. If someone with moderate or severe dementia is given a fall detector, then even it is explained to them, they will quickly forget what it is and its purpose. Consequently they may become anxious about it or discard it.

This was an important step because it crystallised into the two major issues examined in the thesis, and the importance of these issues was subsequently confirmed in discussions with carers and professionals.

These issues were that the performance of fall detectors needs to be improved so that false alarms no longer need to be manually cancelled, and attention must be put into the physical format of the device so that the presence of an unknown device does not itself distress or confuse the wearer.

The problem of performance is applicable to devices for the wider elderly population, although particularly important to those with dementia. It is also a difficult problem, which many people have worked on over several years with only marginal improvements in performance. The review suggested that accelerometer based techniques may be approaching their ultimate performance limit, with further refinement unlikely to produce substantial increases. Any step change in performance would require the introduction of a novel technique.

Chapter 2 looked at what other sensors can, and are, being used alongside accelerometers. New techniques are being investigated, for example, accurate indoor location and velocity would certainly make a difference (Luštrek et al., 2011), and this is likely to be more widely available soon.

Standing back from the problem of fall detection, its underlying purpose is to reduce injury and distress. It is the effect on the wearer which matters, rather than the fall itself. One obvious ramification is that it is far more important to detect injurious falls than non-injurious ones even if they have smaller kinematic signatures.

Extending the idea further, perhaps an ideal "fall detector" would not detect falls at all, but instead detect injury and distress however caused. Conceivably, one might eventually be developed which is sensitive to the biochemical responses of injury or distress. However, based on the review in Chapter 2, and the practical ethos of this thesis, an accelerometer-based device which also measures pulse rate and shape for confirmation was identified as a viable prospect.

The work was restricted to conventional fall detector sites, and specifically the wrist. The Chapter 2 review showed that cardiovascular data is the best prospect because of the variety of information it offers, shown in Table 8.1, which may provide confirmation of a fall identified by an accelerometer. Whilst skin conductivity and temperature are also possible, they are more affected by the environment and provide far less information.

Attribute	Information
Heart rate	Physical exertion
Heart rate modulation	Respiration rate
Heart rate variability	Emotional arousal
Pulse amplitude	Shock

Table 8.1: Cardiovascular attributes which may help to confirm whether a fall has occurred.

Some physiological changes might be easy to detect, such as emotional arousal through heart rate variability, or increased heart rate, but it is not clear how well they indicate injury or distress. But perhaps high precision is not required, and any change accompanying the jolt of a possible fall is enough.

I would have liked to have collected data to properly evaluate whether it was practical. However, participants cannot be deliberately subjected to the serious effects of a fall, and the only possibility would be to fit people likely to fall accidentally with sensors. Accidental falls are rare, and a large number of permanently instrumented participants would be required to collect enough data (Bagalà et al., 2012), which would have been difficult within the available resources and timescale.

This thesis therefore focused on identifying what other physiological information might be obtained to make this approach to fall detection more attractive. I imagined a world in which physiological data was widely used in fall detection. Manufacturers would attempt to maximise the information extracted from the available data, and I thought about what else they might try to use if the devices were equipped with sensors to measure pulse rate.

8.3 Pulse shape studies

The original research goal spawned a new question, "does the pulse waveform shape provide information about the body position?" Three studies were carried out:

1. A study using six convenience participants, following some simple preparatory self-testing, Chapter 3.

2. A larger study to gain a better understanding of the technique and its pitfalls, Chapter 4.

3. A study on elderly people, after a literature review to confirm that they would be an adequate substitute for people with dementia, Chapter 5.

8.3.1 Key findings

The conclusion from this work was that useful information about pose can be obtained from the pulse waveform measured at the wrist using photoplethysmography. This adds to the findings of Linder et al. (2006) and Nocua et al. (2009), that autonomous physiological responses can be used to detect falls and changes in posture, by showing that inferences can be made about static posture too. It also adds to the body of work demonstrating the utility of artificial neural networks for pulse shape analysis (Allen and Murray, 1993; Johansson, 2003; Kurylyak et al., 2013), particularly as the network was a critical element in producing a functioning system.

8.3.2 Limitations

The main limitations were the small sample sizes, and the small number of poses. The sensor proved sensitive to noise and artefacts, but this was probably a consequence of using the wrist where the AC component is small. The majority of photoplethysmography research and clinical practice uses sites such as the fingertip where the AC component is larger. Nevertheless, it was important to use the wrist to examine the problem from the perspective of a practical fall detector. In retrospect, the fingertip would also have proved troublesome because of the small pulse amplitude when the arm is hanging down, seen in Chapter 5. In the context of a sensor for a fall detector, there was a further limitation that the participants kept still to prevent motion artefacts.

As the work progressed my understanding of the issues around pulse shape measurements increased enormously, in particular the effects of the photosensor non-linearity described in Section 4.10. This, coupled with the improvements made to the hardware, software and methods accounts for the substantially better results in the final study, Chapter 5 compared to Chapter 4. It is likely that the results of Chapter 4 would emulate them if repeated with the knowledge gained.

The extraction of pose information from pulse waveform has not been demonstrated for people suffering from great stress or anxiety, which may either be the result of the fall or the dementia, and the effects of vasoactive drugs or cardiovascular conditions is unknown.

8.3.3 Implications

Being able to detect pose from a wrist based device may simply increase its reliability to that of a waist worn system. However, this is important because the wrist is a popular location for fall detectors, particularly as wrist devices can easily be worn at night (Holliday, 2012) although considered less reliable than the waist (Ward, 2012). In addition, there may be many other pieces of useful information which can be extracted from cardiovascular data which may, in combination with the body pose, improve the efficiency much further.

An important aspect of the work was that the components needed for the pulse shape sensor were inexpensive, costing around £40, suggesting that the technology could be incorporated into commercial fall detectors at little cost.

There are practical problems with motion artefacts in an ambulatory photoplethysmography sensor, which were seen in the studies despite participants being encouraged to move as little as possible. However, there is a large body of literature detailing techniques for artefact removal (for example Zhang et al., 2015; Fukushima et al., 2012; Foo, 2006; Alzahrani, 2013; Patterson and Yang, 2010), and further developments in this area are inevitable. Other techniques can also be used to obtain pulse waveforms, such as Doppler velocity and electrical impedance, which may be less prone to artefacts.

A practical device would require machine learning capabilities to tune itself to the wearer's physiology although the mechanics of how this would be done were not explored in the studies. Classifier training was required by several experimental fall detector studies, such as Zhang et al. (2006); Zhao et al. (2012); Mitchell et al. (2012). Whilst supervised training of development systems is possible using simulated fall data, this is problematic in a production system if it requires adaption to the characteristics of a frail wearer.

In these cases, unsupervised learning is conceivable because the fall detector may function by detecting acceleration events outside of the normal range. However a system utilising pulse shape needs supervised training because the supine pose occurs normally. Perhaps it is as simple as the carer periodically informing the system when the wearer is supine, standing or sitting. A fall detector utilising physiological signs of distress, however, would face the same problems with training as accelerometer based algorithms.

These studies did not completely answer the question of how to reduce the false alarm rate of fall detectors, but pointed to a possible route which challenges the reliance on entirely accelerometer-based techniques, and the positive results suggest further research into using physiological data for fall detection.

8.4 Design study

Building a technically superior device is of little consequence if people will not use it, and having focused on the wrist for the pulse shape studies, the thesis examined how it could be packaged in a practical manner for people with dementia. The thesis reported the following studies:

1. Three focus groups involving formal and informal carers of people with dementia to examine the overall requirements, Chapter 6.

2. Semi-structured interviews of six carers to evaluate an outline design, Chapter 7.

The ordering of the pulse shape work and the design study was important – if the design study had preceded the pulse shape study then there may have been a different outcome since the pulse shape work mandated a sensor which touched the skin. However, without steps to improve the ability of fall detectors to correctly identify falls, there would be little point in a device for people with dementia.

Conversely, there is an argument that if the design study had preceded the pulse shape work, then a better understanding of the contextual requirements of the fall detector may have led to a different approach being taken. However, whilst many researchers explore a variety of sites for fall detectors, commercial devices are almost exclusively confined to the waist, wrist and neck, and the research literature confirms the popularity of the wrist (Holliday, 2012; FARSEEING Consortium, 2013; Holzinger et al., 2010; Mahoney and Mahoney, 2010). It is therefore likely that the design study would have still produced a wrist-worn device.

8.4.1 Key Findings

The conclusion of the design study was that for mild dementia a smart watch, or similar device, might be used. For more advanced dementia, a novel disk-shaped device which fitted underneath an existing watch was proposed. The key factor in the acceptability of the device is its thickness, which is linked to its power consumption.

The information from carers strongly confirmed the widely held view that visible lifestyle changes are difficult to implement for people with dementia.

A minor, but nevertheless surprising, finding was that a battery life of only two weeks was sufficient, since it challenges the view expressed in Holliday (2012) that even three or six months is too short.

However, this discrepancy is explained by the difference in views of the informal carers who can change a battery and professional staff who had to schedule appointments to do so. In addition, hearing aids are common amongst the elderly and carers were used to changing their batteries at similar intervals.

8.4.2 Limitations

This work shared a limitation of the pulse shape work, in having only a small number of participants. The prototypes for the evaluation were very basic, and other parts of the system such as the base station were only discussed for context and not in detail. It was an exploratory study to evaluate the feasibility of a concept, and appropriate not to consider these other features until a later stage.

8.4.3 Implications

This work to some extent supports the view that the wrist is the preferred location for a fall detector (Holliday, 2012; FARSEEING Consortium, 2013; Holzinger et al., 2010; Mahoney and Mahoney, 2010). However, the study did not allow full freedom of location for the fall detector because of functional considerations, such as the requirement for the pulse sensor to have contact with skin. This meant that the waist and the neck were not viable choices, even though the focus groups occasionally touched upon them.

It emulates other pieces of work which proposed that fall detectors be incorporated into watches (Degen et al., 2003), or other familiar items such as hearing aids (Lindemann et al., 2005), shoes (Sim et al., 2011), and strongly supports the findings of Mahoney and Mahoney (2010); Bergmann and McGregor (2011) that the devices should be discrete and not intrusive.

Whilst participants did not think that the device should be difficult to remove, some were enthusiastic about concealing it from the wearer, and the nature of the discrete device provides some blurring between concealment and encouraging the wearer to forget about the device. This raises ethical issues, which were not explored but are often present in assistive living monitoring projects (Mahoney and Mahoney, 2010).

The successful outcome of the study confirmed the validity of the proposition by Orpwood (2004) that carers, rather than the sufferers of dementia, should be used in the early stages of the design process for assistive living products for people with dementia because of their intimate understanding of the people that they care for.

8.5 Contributions

This work added to the body of knowledge in several areas, which are summarised in Table 8.2. These contributions all build on the work of other researchers, who are cited in the relevant sections. In addition, preliminary work suggested two potentially worthwhile research ideas which were not progressed for lack of time. These were to use a robot arm to ensure repeatability in fall detector testing (Section 2.1.2), and to examine ankle kinematics following a possible fall as a novel detection technique (Section 2.4.1).

Contribution	Sections
Characteristics of an ideal wearable fall detector, what it should detect and how it should operate internally	2.3, 2.5, 2.6, 8.2
Review of sensors which could be incorporated into a wearable fall detector	2.4
Using photoplethysmographic pulse waveform shape to determine body pose	Chapters 3–5
Optimising photoplethysmographic pulse shape sensor design – filters, illumination versus photosensor response, optical wavelength etc.	4.6, 4.7, 4.10–4.12
Elderly people as a substitute for people with dementia in pulse shape studies	5.1
Issues affecting the usability of fall detectors for people with dementia	6.8–6.11
Identification and acceptability of devices specifically for people with dementia – smart watch for mild dementia and underwatch device for more severe dementia	6.8–6.11, 7.2–7.6
Practical considerations in the design of an underwatch fall detector	7.1, Appendix C

Table 8.2: Areas where this thesis has made contributions to knowledge.

8.6 Future directions

There is much work which needs to be done to examine the effectiveness of using physiological responses in fall detectors. Testing is key to this, and should focus on cardiovascular data, considering pulse shape, heart rate and factors which can be derived from it and possibly pulse amplitude. One approach would be to use a tilt table, as a way of better controlling the poses.

This would also allow the technique pioneered by Bisdorff et al. (1999), described in Section 2.1.1, of dropping the tilt table from a few degrees above horizontal to horizontal in a safe fashion, to be extended to produce the immediate physiological responses to a fall which are absent in deliberately simulated falls.

If this work validated the effectiveness of physiological responses to aid fall detection within the laboratory, the next step would be to extend it into more realistic conditions by instrumenting people who were prone to falling with the sensor. Many researchers have used participants with progressive supranuclear palsy to gather accelerometer data since this disease causes serious gait and balance impairment (Palmerini et al., 2015; Bagalà et al., 2012; Kangas et al., 2011), and this could be done for physiological data.

During the period over which the work was undertaken, smart bands and watches have increased in popularity and programmable wrist-worn devices containing both kinematic and photoplethysmography sensors have become widely available.

Whilst the photoplethysmography sensors are unable to produce more detailed information than pulse rate, liaison with manufacturers may provide access to far more functionality. The widespread and increasing use of these devices presents an opportunity to recruit and gather data from a large user population, and at the same time offer the scope to easily add fall detection to a device which is purchased for another purpose such as fitness or sleep monitoring. In addition, in the same way that many elderly people currently use wrist watches, a subsequent generation will probably be just as comfortable with these intelligent wrist worn devices which can be programmed to provide many assistive living functions.

If the use of physiological data is confirmed as a credible signature for fall detection when used alongside kinematic sensors, then it can be developed into either a smart band or smart watch, or an underwatch device, depending upon the target population for the fall detector.

8.7 Conclusion

This thesis has sought to balance the study of technical aspects of fall detection for people with dementia with practical ones, since neither can be successful in isolation.

Wearable fall detectors, as they currently exist, do not detect falls with sufficient reliability for people with moderate or severe dementia. They are too intrusive and the wearer has to manually eliminate false alarms. Falls are a problem because of the distress and injury that they cause, but a perfect device might look for the outcome – distress and injury – rather than the fall. The best physiological data for a wrist worn device is the pulse since there are well-documented methods for extracting several pieces of information from it. This thesis demonstrated that it is also possible to obtain body pose information from it.

Once AD or related dementias have taken hold, making changes to the person's life is difficult since they are unable to assimilate new information. It is therefore important to introduce the device into their lives as early as possible, and the device should be unobtrusive if introduced in the later stages. The level of intrusion can be reduced by mounting the device underneath an existing wrist watch, especially as many elderly people routinely wear watches.

These two together ideas together, a discrete wearable device which can maximise reliability in fall detection by using cardiovascular data alongside kinematic, provides the first steps towards a practical wearable fall detector for people with moderate to severe dementia.

Appendix A

Arduino source code

A.1 Arduino source code for first study, with 6 participants

This is the firmware for the pulse sensor used in Section 3.3. It uses the Arduino's built-in ADC and reads it out at 500 samples per second. It attaches a timestamp to it and transmits it to the laptop.

```
// Written by Jason Leake
// License: Creative Commons Attribution 4.0 International Public
    License

const int PULSE_PIN = 1;            // Pulse sensor analogue signal
const int BLINK_PIN = 13;           // LED pin
const int COUNT_UP = 100;           // LED on or off every COUNT_UP
    points read
volatile int flag = 0;

int blink = HIGH;
int count = 0;

// Data output format is "Pxxxxxx,yyy\r\n"
//
// 13 digits, ~130 bits
// 880 outputs per second maximum

void setup() {
  pinMode(BLINK_PIN,OUTPUT);
  pinMode(PULSE_PIN,INPUT);
  analogReference(EXTERNAL);
  Serial.begin(115200);
```

```
  // Setup interrupts using timer 1 which is not otherwise used
  noInterrupts();
  TCCR1A = 0;
  TCCR1B = 0;
  TCNT1  = 0;
  OCR1A = 300;     // compare match register.  500 points per second
  TCCR1B |= (1 << WGM12);   // CTC mode
  TCCR1B |= (1 << CS12);    // 256 prescaler
  TIMSK1 |= (1 << OCIE1A);  // Enable timer compare interrupt
  interrupts();
}

ISR(TIMER1_COMPA_vect) {
  flag = 1;
}

void loop() {
  // If timer has gone off then reset its flag and read and then
  // output the data
  if (flag) {
    flag = 0;
    Serial.print("P");
    unsigned long time = millis();
    Serial.print(time);
    Serial.print(",");
    Serial.println(analogRead(PULSE_PIN));

    // Handle flashing of LED
    if (++count >= COUNT_UP) {
      digitalWrite(BLINK_PIN, blink);
      blink = (blink == HIGH) ? LOW : HIGH;
      count = 0;
    }
  }
}
```

A.2 Arduino source code for the final study

This is the software for the pulse sensor used in the study described in Chapter 5. It reads an MCP3301 ADC using hardware SPI at 1500 samples per second, frames it with a timestamp and checksum for transmission over the serial link to the laptop. The signal lines to and from the ADC are inverted by an opto-isolator. The increased data rate required the millisecond resolution previously used to be uprated to microsecond resolution.

The SPI format is dictated by the MCP3301 design. After the chip select enables the device, it samples the signal voltage on the rising edge of the first clock and the data is clocked out on the falling edges of the clock starting with the sign bit. As the clock is inverted by the isolators from the Arduino's perspective, the data appears on rising edge of the next clock. For debugging purposes all 16 bits read by the SPI library are transmitted to the laptop as read, and the top 3 stripped off on arrival.

```
// Written by Jason Leake
// License: Creative Commons Attribution 4.0 International Public
    License

#include <SPI.h>

static volatile bool sendData = true;

// Debugging flags:
// Set this flag to false to produce ASCII output for debugging
const bool BINARY = true;

// Chip select line
const int CHIP_SELECT = 3;

/*****************************************************************
    */
// Setup serial port, SPI and timer interrupt
void setup() {

  pinMode(CHIP_SELECT, OUTPUT);

  // Setup interrupts using timer 1, which is not otherwise used
  noInterrupts();
  TCCR1A = 0;
  TCCR1B = 0;
  TCNT1  = 0;
  OCR1A = 1333;              // 1500 samples per second

  TCCR1B |= (1 << WGM12);    // CTC mode
  TCCR1B |= (1 << CS11);     // 8 prescaler
```

```
  TIMSK1 |= (1 << OCIE1A);  // Enable timer compare interrupt
  interrupts();

  SPI.begin();
  SPI.setClockDivider(SPI_CLOCK_DIV32); // 16 MHz clock. 0.5 MHz
      data clock
  SPI.setDataMode(SPI_MODE2);
  SPI.setBitOrder(MSBFIRST);
  Serial.begin(115200);
}

/*****************************************************************
    */
// Set flag whenever interrupt occurs to tell loop() to read a
    sample
// The effect of this is to set sendData true every 666.666 uS. The
    main
// program loop reads the ADC when this becomes true.
ISR(TIMER1_COMPA_vect) {
  sendData = true;
}

/*****************************************************************
    */
// Calculate CRC-8
byte checksum(const byte* buffer, unsigned bufferLength) {
  //
  // CRC-8 lookup table
  //
  // The table below was generated using pycrc, which can
  // be found at https://pycrc.org/
  // python pycrc.py --model crc-8 --generate=table
  static const byte TABLE[] = {
    0x00, 0x07, 0x0e, 0x09, 0x1c, 0x1b, 0x12, 0x15, 0x38,
    0x3f, 0x36, 0x31, 0x24, 0x23, 0x2a, 0x2d, 0x70, 0x77,
    0x7e, 0x79, 0x6c, 0x6b, 0x62, 0x65, 0x48, 0x4f, 0x46,
    0x41, 0x54, 0x53, 0x5a, 0x5d, 0xe0, 0xe7, 0xee, 0xe9,
    0xfc, 0xfb, 0xf2, 0xf5, 0xd8, 0xdf, 0xd6, 0xd1, 0xc4,
    0xc3, 0xca, 0xcd, 0x90, 0x97, 0x9e, 0x99, 0x8c, 0x8b,
    0x82, 0x85, 0xa8, 0xaf, 0xa6, 0xa1, 0xb4, 0xb3, 0xba,
    0xbd, 0xc7, 0xc0, 0xc9, 0xce, 0xdb, 0xdc, 0xd5, 0xd2,
    0xff, 0xf8, 0xf1, 0xf6, 0xe3, 0xe4, 0xed, 0xea, 0xb7,
```

```
    0xb0, 0xb9, 0xbe, 0xab, 0xac, 0xa5, 0xa2, 0x8f, 0x88,
    0x81, 0x86, 0x93, 0x94, 0x9d, 0x9a, 0x27, 0x20, 0x29,
    0x2e, 0x3b, 0x3c, 0x35, 0x32, 0x1f, 0x18, 0x11, 0x16,
    0x03, 0x04, 0x0d, 0x0a, 0x57, 0x50, 0x59, 0x5e, 0x4b,
    0x4c, 0x45, 0x42, 0x6f, 0x68, 0x61, 0x66, 0x73, 0x74,
    0x7d, 0x7a, 0x89, 0x8e, 0x87, 0x80, 0x95, 0x92, 0x9b,
    0x9c, 0xb1, 0xb6, 0xbf, 0xb8, 0xad, 0xaa, 0xa3, 0xa4,
    0xf9, 0xfe, 0xf7, 0xf0, 0xe5, 0xe2, 0xeb, 0xec, 0xc1,
    0xc6, 0xcf, 0xc8, 0xdd, 0xda, 0xd3, 0xd4, 0x69, 0x6e,
    0x67, 0x60, 0x75, 0x72, 0x7b, 0x7c, 0x51, 0x56, 0x5f,
    0x58, 0x4d, 0x4a, 0x43, 0x44, 0x19, 0x1e, 0x17, 0x10,
    0x05, 0x02, 0x0b, 0x0c, 0x21, 0x26, 0x2f, 0x28, 0x3d,
    0x3a, 0x33, 0x34, 0x4e, 0x49, 0x40, 0x47, 0x52, 0x55,
    0x5c, 0x5b, 0x76, 0x71, 0x78, 0x7f, 0x6a, 0x6d, 0x64,
    0x63, 0x3e, 0x39, 0x30, 0x37, 0x22, 0x25, 0x2c, 0x2b,
    0x06, 0x01, 0x08, 0x0f, 0x1a, 0x1d, 0x14, 0x13, 0xae,
    0xa9, 0xa0, 0xa7, 0xb2, 0xb5, 0xbc, 0xbb, 0x96, 0x91,
    0x98, 0x9f, 0x8a, 0x8d, 0x84, 0x83, 0xde, 0xd9, 0xd0,
    0xd7, 0xc2, 0xc5, 0xcc, 0xcb, 0xe6, 0xe1, 0xe8, 0xef,
    0xfa, 0xfd, 0xf4, 0xf3
  };

  byte checksum = 0;
  while (bufferLength--) {
    unsigned index = checksum ^ *buffer++;
    index = index & 0xff;
    checksum = TABLE[index];
  }
  return checksum;
}

/*****************************************************************
    */
// Main loop
void loop() {

  // Fields in the output
  enum {
    IDLETTER = 0,
    TIMESTAMPH = 1,
    TIMESTAMPL = 2,
    DATUMH = 3,
```

```
  DATUML = 4,
  CHECKSUM = 5,
};

if (sendData) {
  sendData = false;
  // Read timestamp into this so we can pick out
  // the bottom two bytes
  union {
    unsigned long ul;
    // Arduino is little endian, so significance of
    // byte increased with address
    struct {
      byte l;
      byte h;
      // The upper two bytes are going to be ignored
      byte u1;
      byte u2;
    };
  } timestamp;
  timestamp.ul = micros();

  // This is where the output is built
  byte buffer[6];

  // IDLETTER is P for a wrist device, F for a fingertip device
  buffer[IDLETTER] = 'F';
  // Pick off the two least significant bytes. Data transmitted in
  // network order - i.e. most significant byte first.
  buffer[TIMESTAMPH] = timestamp.h;
  buffer[TIMESTAMPL] = timestamp.l;

  // Chip select high. Signal to ADC is ~chip select, but is
     inverted
  // by Si8711 isolator
  digitalWrite(CHIP_SELECT, HIGH);
  // Received data values are inverted by Si8711 isolator
  buffer[DATUMH] = ~SPI.transfer(0);
  buffer[DATUML] = ~SPI.transfer(0);
  // Deslect ADC chip
  digitalWrite(CHIP_SELECT, LOW);
  // Calculate checksum of 'P' (or 'F'), timestamp and datum.
```

```
    // buffer-1 because the last field is the checksum itself
    // which is not checksummed
    buffer[CHECKSUM] = checksum(buffer, sizeof(buffer)-1);

    // Send to serial port
    // If BINARY is true then output in binary. If false then output
    // in ASCII with a long delay between values, for debugging
    if (BINARY) {
      for (unsigned index = 0; index < sizeof(buffer); index++) {
        Serial.write(buffer[index]);
      }
    }
    else {
      Serial.print(timestamp.ul & 0xffff);
      Serial.print(" ");
      // Represent two bytes as a short
      union {
        unsigned short s;
        struct {
          byte l;
          byte h;
        };
      } datum;
      datum.h = buffer[DATUMH];
      datum.l = buffer[DATUML];
      // Buffer for conversion
      char numBuf[20];
      snprintf(numBuf, sizeof(buffer), "%x %d", datum.s, buffer[
          CHECKSUM]);
      // snprintf doesn't add null if it uses last char in buffer
      numBuf[sizeof(numBuf)-1] = '\0';
      Serial.println(numBuf);
      delay(100);
    }
    Serial.flush();
  }
}
```

Appendix B

Attribute extraction source code

This is the source code used to compute the different pulse waveform attributes in Section 3.3. Each pulse waveform is represented by a `Heartbeat` object, which contains a map of the values of each feature. These are filled in by the `addValue()` method of objects sub-classed from `HeartbeatFeatureAggregator` representing each feature.

When the features are formatted into the Weka .arff file they become attributes. Both terms are widely used, as are *variable* and *field*, but the rest of this thesis consistently uses *attribute* to avoid confusion.

Listing B.1: HeartbeatFeatureAggregator.java

```
package features;

import averagePulse.Constants;
import averagePulse.ProcessingStage;
import graphics.HeartbeatPlotter;
import java.util.EnumMap;
import java.util.Map;
import settings.Settings;
import types.FeatureEnum;
import types.Heartbeat;

/**
 * Superclass for heartbeat data aggregators
 *
 * @author Jason Leake
 */
abstract public class HeartbeatFeatureAggregator extends Aggregator
    {
```

```
private static int counter = 0;
protected static final double LOWER = 0.15;
protected static final double UPPER = 0.95;

public enum Characteristics {

    LOWER,
    UPPER,
    RISE_START,
    RISE_END,
    FALL_START,
    FALL_END,
    FIRST_MAXIMUM
};
private final FeatureEnum featureEnum;

/**
 * Constructor.
 *
 * @param stage processing stage that this aggregator is used in
 * @param feature feature that the object aggregates
 */
protected HeartbeatFeatureAggregator(ProcessingStage stage,
        FeatureEnum feature) {
    super(stage, feature.getFileAcceptableName());
    featureEnum = feature;
}

/**
 * Get feature that this aggregator measures
 *
 * @return feature
 */
public FeatureEnum getFeatureEnum() {
    return featureEnum;
}

/**
 * Extract value from heartbeat and add it to aggregate
 *
 * @param heartbeat
```

```
 */
abstract public void addValue(Heartbeat heartbeat);

/**
 * Get the decay time of the heartbeat
 *
 * @param heartbeat heartbeat to examine
 * @param minimum maximum value as proportion of amplitude,
    start of decay
 * @param maximum minimum value as proportion of amplitude, end
    of decay
 * @return decay time in milliseconds
 */
protected double getDecayTime(Heartbeat heartbeat, double
    minimum,
        double maximum) {
    return getProperDecay(heartbeat, minimum, maximum);

}

/**
 * Get the length of the heartbeat
 *
 * @param heartbeat heartbeat to examine
 * @param minimum lower value to look for
 * @return decay time in milliseconds
 */
protected double getLength(Heartbeat heartbeat, double minimum)
    {
    Heartbeat unitAmplitude = heartbeat.toUnitAmplitude();
    int startMilliseconds;
    if (unitAmplitude.get(0).value > minimum) {
        startMilliseconds = 0;
    } else {
        startMilliseconds = unitAmplitude.getFirstByValue(
            minimum).milliseconds;
    }
    int endMilliseconds = unitAmplitude.getLastByValue(minimum).
        milliseconds;
    double length = (double) endMilliseconds - (double)
        startMilliseconds;
    if (!check(heartbeat, length, "length")) {
```

```
        throw new RuntimeException("Check␣failure␣" + length + "
            ␣"
                + startMilliseconds + "␣"
                + endMilliseconds);

    }
    return length;
}

/**
 * Get rise between normalised limits
 *
 * @param heartbeat heartbeat to measure
 * @param minimum lower limit
 * @param maximum upper limit
 * @return heartbeat rise time
 */
protected double getRiseTime(Heartbeat heartbeat, double minimum
    , double maximum) {
    return getProperRise(heartbeat, minimum, maximum);

}

/**
 * Generate a map of the characteristics of this heartbeat.
     These are the
 * lower limit, the upper limit, where the rise starts and ends,
      and where
 * the fall starts and ends
 *
 * @param heartbeat heartbeat to check
 * @return map of characteristics for this heartbeat
 */
public static Map<Characteristics, Double> getCharacteristics(
    Heartbeat heartbeat) {
    Heartbeat unitAmplitude = heartbeat.toUnitAmplitude();

    Map<Characteristics, Double> characteristics = new EnumMap
        <>(Characteristics.class);
    double minimum = heartbeat.getFirstMinimum().value;
    double amplitude = heartbeat.getFirstMaximum().value -
        minimum;
```

```
    characteristics.put(Characteristics.LOWER, LOWER * amplitude
        + minimum);
    characteristics.put(Characteristics.UPPER, UPPER * amplitude
        + minimum);
    characteristics.put(Characteristics.RISE_START,
            (double) unitAmplitude.getFirstByValue(LOWER).
                milliseconds);
    characteristics.put(Characteristics.RISE_END,
            (double) unitAmplitude.getFirstByValue(UPPER).
                milliseconds);
    characteristics.put(Characteristics.FALL_START,
            (double) unitAmplitude.getLastByValue(UPPER).
                milliseconds);
    characteristics.put(Characteristics.FALL_END,
            (double) unitAmplitude.getLastByValue(LOWER).
                milliseconds);
    characteristics.put(Characteristics.FIRST_MAXIMUM,
            (double) unitAmplitude.getFirstMaximum().
                milliseconds);
    return characteristics;
}

/**
 * Get overall length of heartbeat
 *
 * @param heartbeat heartbeat to examine
 * @return overall length of heartbeat
 */
protected double getOverallLength(Heartbeat heartbeat) {
    return heartbeat.getLast().milliseconds - heartbeat.get(0).
        milliseconds;
}

/**
 * Check that the value is sensible - i.e. not negative
 *
 * @param heartbeat
 * @param value
 * @param valueName
 * @return true if ok
 */
```

```
private boolean check(Heartbeat heartbeat, double value, String
    valueName) {
     if (value < 0.0) {
         new HeartbeatPlotter(String.format("%s␣%.2f",
                  valueName, value / 1000), "run",
                  Constants.LOG_DIRECTORY + Constants.SEPARATOR +
                      "check"
                  + Integer.toString(counter++)).plot(heartbeat);
         return false;
     }
     return true;
}

/**
 * Get the decay time of the heartbeat
 *
 * @param heartbeat heartbeat to examine
 * @param minimum maximum value as proportion of amplitude,
 *     start of decay
 * @param maximum minimum value as proportion of amplitude, end
 *     of decay
 * @return decay time in milliseconds
 */
private double getProperDecay(Heartbeat heartbeat, double
    minimum,
         double maximum) {
     Heartbeat unitAmplitude = heartbeat.toUnitAmplitude();
     int startMilliseconds = unitAmplitude.getLastByValue(maximum
         ).milliseconds;
     int endMilliseconds = unitAmplitude.getLastByValue(minimum).
         milliseconds;
     if (endMilliseconds < startMilliseconds) {
         endMilliseconds = unitAmplitude.getLast().milliseconds;
     }
     double decay = endMilliseconds - startMilliseconds;
     if (!check(heartbeat, decay, "decay")) {
         throw new RuntimeException("Check␣failure␣" + decay + "␣
             "
                  + startMilliseconds + "␣"
                  + endMilliseconds);
     }
     return decay;
```

```java
}

/**
 * Get rise between normalised limits
 *
 * @param heartbeat heartbeat to measure
 * @param minimum lower limit
 * @param maximum upper limit
 * @return heartbeat rise time
 */
private double getProperRise(Heartbeat heartbeat, double minimum
    , double maximum) {

    Heartbeat unitAmplitude = heartbeat.toUnitAmplitude();
    int startMilliseconds;
    if (unitAmplitude.get(0).value > minimum) {
        startMilliseconds = 0;
    } else {
        startMilliseconds = unitAmplitude.getFirstByValue(
            minimum).milliseconds;
    }
    int riseEndMilliseconds = unitAmplitude.getFirstByValue(
        maximum).milliseconds;

    double rise = riseEndMilliseconds - startMilliseconds;
    if (!check(heartbeat, rise, "rise")) {
        throw new RuntimeException("Check failure " + rise + " "
                + startMilliseconds + " "
                + riseEndMilliseconds);
    }
    return rise;
}

/**
 * Get rise integral for unit amplitude heartbeat
 *
 * @param heartbeat heartbeat data to process
 * @param minimum minimum amplitude for start as fraction
 * @param maximum maximum amplitude for end as fraction
 * @return integral rise integral
 */
double getRiseIntegral(Heartbeat heartbeat, double minimum,
```

```
    double maximum) {
    Heartbeat unitAmplitude = heartbeat.toUnitAmplitude();
    int start;
    if (unitAmplitude.get(0).value > minimum) {
        start = 0;
    } else {
        start = unitAmplitude.getFirstByIndex(minimum);
    }
    int end = unitAmplitude.getFirstByIndex(maximum);
    if (end < start) {
        throw new RuntimeException("End time before start time")
            ;
    }

    double integral = 0;
    for (int index = start; index < end; index++) {
        double value = heartbeat.get(index).value;
        if (value < 0) {
            throw new RuntimeException("Negative value " +
                heartbeat.get(index));
        }
        integral += value;
    }
    return integral;
}

/**
 * Get decay integral for unit amplitude heartbeat
 *
 * @param heartbeat pulse waveform to examine
 * @param minimum maximum value as proportion of amplitude,
     start of decay
 * @param maximum minimum value as proportion of amplitude, end
     of decay
 * @return integral integral value
 */
double getDecayIntegral(Heartbeat heartbeat, double minimum,
    double maximum) {

    Heartbeat unitAmplitude = heartbeat.toUnitAmplitude();
    int start = unitAmplitude.getLastByIndex(maximum);
    int end = unitAmplitude.getLastByIndex(minimum);
```

```
        if (end < start) {
            end = unitAmplitude.size() - 1;
        }
        double integral = 0;
        for (int index = start; index < end; index++) {
            double value = heartbeat.get(index).value;
            if (value < 0) {
                throw new RuntimeException("Negative value " +
                    heartbeat.get(index));
            }

            integral += value;
        }
        return integral;

    }

}
```

Listing B.2: AreaRatioFeature.java

```java
package features;

import averagePulse.ProcessingStage;
import settings.Settings;
import types.FeatureEnum;
import types.Heartbeat;
import types.TimestampedValue;

/**
 * Calculates the ratio of the integral of the pulse rise to the
    integral of the
 * decay
 *
 * @author Jason Leake
 */
public class AreaRatioFeature extends HeartbeatFeatureAggregator {

    /**
     * Constructor
     *
     * @param stage Processing stage
     */
    public AreaRatioFeature(ProcessingStage stage) {
        super(stage, FeatureEnum.AREA_RATIO);
    }

    /**
     * Add value
     *
     * @param heartbeat heartbeat to extract value from
     */
    @Override
    public void addValue(Heartbeat heartbeat) {
        addValue(getRiseIntegral(heartbeat, LOWER, UPPER)
                / getDecayIntegral(heartbeat, LOWER, UPPER));
    }
}
```

Listing B.3: DecayTimeFeature.java

```java
package features;

import averagePulse.ProcessingStage;
import types.FeatureEnum;
import types.Heartbeat;

/**
 * Computes the pulse decay time
 *
 * @author Jason Leake
 */
public class DecayTimeFeature extends HeartbeatFeatureAggregator {

    /**
     * Constructor
     *
     * @param stage processing stage
     */
    public DecayTimeFeature(ProcessingStage stage) {
        super(stage, FeatureEnum.DECAY_TIME);
    }

    /**
     * Add decay value
     *
     * @param heartbeat heartbeat to extract decay value from
     */
    @Override
    public void addValue(Heartbeat heartbeat) {
        addValue(getDecayTime(heartbeat, LOWER, UPPER));
    }
}
```

Listing B.4: DecayTimePulseLengthRatioFeature.java

```java
package features;

import averagePulse.ProcessingStage;
import types.FeatureEnum;
import types.Heartbeat;

/**
 * Computes the ratio of the pulse decay time to the pulse length
 *
 * @author Jason Leake
 */
public class DecayTimePulseLengthRatioFeature extends
    HeartbeatFeatureAggregator {

    /**
     * Constructor
     *
     * @param stage Processing stage
     */
    public DecayTimePulseLengthRatioFeature(ProcessingStage stage) {
        super(stage, FeatureEnum.DECAY_LENGTH_RATIO);
    }

    /**
     * Add value
     *
     * @param heartbeat heartbeat to extract value from
     */
    @Override
    public void addValue(Heartbeat heartbeat) {
        addValue(getDecayTime(heartbeat, LOWER, UPPER)
                / getLength(heartbeat, LOWER));
    }
}
```

Listing B.5: PulseLengthFeature.java

```
package features;

import averagePulse.ProcessingStage;
import types.FeatureEnum;
import types.Heartbeat;

/**
 * Computes the pulse length
 *
 * @author Jason Leake
 */
public class PulseLengthFeature extends HeartbeatFeatureAggregator {

    /**
     * Constructor
     *
     * @param stage processing stage
     */
    public PulseLengthFeature(ProcessingStage stage) {
        super(stage, FeatureEnum.LENGTH);
    }

    /**
     * Add length value
     *
     * @param heartbeat heartbeat to extract length value from
     */
    @Override
    public void addValue(Heartbeat heartbeat) {
        addValue(getLength(heartbeat, LOWER));
    }
}
```

Listing B.6: NormalisedDecayAreaFeature.java

```java
package features;

import averagePulse.ProcessingStage;
import static features.HeartbeatFeatureAggregator.LOWER;
import settings.Settings;
import types.FeatureEnum;
import types.Heartbeat;
import types.TimestampedValue;

/**
 * Calculates the integral of the normalised pulse decay
 *
 * @author Jason Leake
 */
public class NormalisedDecayAreaFeature extends
    HeartbeatFeatureAggregator {

    /**
     * Constructor
     *
     * @param stage processing stage
     */
    public NormalisedDecayAreaFeature(ProcessingStage stage) {
        super(stage, FeatureEnum.NORMALISED_DECAY_INTEGRAL);
    }

    /**
     * Add value
     *
     * @param heartbeat heartbeat to extract value from
     */
    @Override
    public void addValue(Heartbeat heartbeat) {
        double decayIntegral = getDecayIntegral(heartbeat, LOWER,
            UPPER);

        TimestampedValue maximum = heartbeat.getFirstMaximum();
        TimestampedValue minimum = heartbeat.getFirstMinimum();
        double range = maximum.value - minimum.value;
        double normalisedHeight = decayIntegral / range;
```

```
        double period = heartbeat.getLast().milliseconds
                - heartbeat.get(0).milliseconds;

        double normalisedWidth = (double) (Settings.
            NORMALISED_HEARTBEAT_WIDTH_MS)
                * normalisedHeight / period;

        addValue(normalisedWidth);
    }
}
```

Listing B.7: RiseTimeDecayTimeRatioFeature.java

```java
package features;

import averagePulse.ProcessingStage;
import types.FeatureEnum;
import types.Heartbeat;

/**
 * Calculates the ratio of the rise time to the decay time
 *
 * @author Jason Leake
 */
public class RiseTimeDecayTimeRatioFeature extends
    HeartbeatFeatureAggregator {

    /**
     * Constructor
     *
     * @param stage Processing stage
     */
    public RiseTimeDecayTimeRatioFeature(ProcessingStage stage) {
        super(stage, FeatureEnum.RISE_TIME_DECAY_TIME_RATIO);
    }

    /**
     * Add value
     *
     * @param heartbeat heartbeat to extract value from
     */
    @Override
    public void addValue(Heartbeat heartbeat) {
        addValue(getRiseTime(heartbeat, LOWER, UPPER)
                / getDecayTime(heartbeat, LOWER, UPPER));
    }
}
```

Listing B.8: RiseTimeFeature.java

```java
package features;

import averagePulse.ProcessingStage;
import types.FeatureEnum;
import types.Heartbeat;

/**
 * Compute the pulse rise time
 *
 * @author Jason Leake
 */
public class RiseTimeFeature extends HeartbeatFeatureAggregator {

    /**
     * Constructor
     *
     * @param stage processing stage
     */
    public RiseTimeFeature(ProcessingStage stage) {
        super(stage, FeatureEnum.RISE_TIME);
    }

    /**
     * Add rise time value
     *
     * @param heartbeat heartbeat to extract rise value from
     */
    @Override
    public void addValue(Heartbeat heartbeat) {
        addValue(getRiseTime(heartbeat, LOWER, UPPER));
    }
}
```

Listing B.9: RiseTimePulseLengthRatioFeature.java

```java
package features;

import averagePulse.ProcessingStage;
import types.FeatureEnum;
import types.Heartbeat;

/**
 * Calculates the ratio of the rise time to the overall pulse length
 *
 * @author Jason Leake
 */
public class RiseTimePulseLengthRatioFeature extends
    HeartbeatFeatureAggregator {

    /**
     * Constructor
     *
     * @param stage Processing stage
     */
    public RiseTimePulseLengthRatioFeature(ProcessingStage stage) {
        super(stage, FeatureEnum.RISE_TIME_PULSE_LENGTH_RATIO);
    }

    /**
     * Add value
     *
     * @param heartbeat heartbeat to extract value from
     */
    @Override
    public void addValue(Heartbeat heartbeat) {
        addValue(getRiseTime(heartbeat, LOWER, UPPER) /
                getLength(heartbeat, LOWER));
    }
}
```

Listing B.10: TotalPeriodFeature.java

```
package features;

import averagePulse.ProcessingStage;
import types.FeatureEnum;
import types.Heartbeat;

/**
 * Aggregates the overall pulse length
 *
 * @author Jason Leake
 */
public class TotalPeriodFeature extends HeartbeatFeatureAggregator {

    /**
     * Constructor
     *
     * @param stage Processing stage
     */
    public TotalPeriodFeature(ProcessingStage stage) {
        super(stage, FeatureEnum.TOTAL_PERIOD);
    }

    /**
     * Add length value
     *
     * @param heartbeat heartbeat to extract length value from
     */
    @Override
    public void addValue(Heartbeat heartbeat) {
        addValue(getOverallLength(heartbeat));
    }
}
```

Appendix C

Underwatch design considerations

This appendix discusses some of the electronic design considerations for the underwatch fall detector. To develop a practical device would be a considerable amount of work, but an outline sketch design can be prepared, as shown in Figure C-1. The SPI connections are one or two data lines and a clock, and a chip select, which is shown separately since it is driven from a separate GPIO pin.

C.1 Microcontroller and communications subsystem

The heart of the device is the monolithic microcontroller and RF communications chip. The device considered for this outline was a Nordic Semiconductor nRF51422 system on a chip since it was designed for coin cell powered devices and equipped with ANT communications up to 4 dBm output power. Whilst 4 dBm is sufficient to provide a 30 m range the poor antenna and screening due to the wearer and watch may reduce it considerably. It is available in tiny packages, ranging from 6 mm × 6 mm QFN48 package to 3.8 mm × 3.8 mm WLSCP (Nordic Semiconductor, 2014). The device contains an Arm Cortex M0 core with 16 kB RAM and 256kB flash memory, and peripherals which include battery monitoring, temperature sensing and GPIO pins. It supports SPI in both master and slave mode but the interface is slow, with a maximum speed of 4 MHz.

The microcontroller consumes 0.6 µA to 2.6 µA in idle mode, according to how much of the device is powered up (Nordic Semiconductor, 2014).

Several external capacitors are needed, along with a 16 MHz crystal, a balun/harmonic filter and an antenna with a second crystal advised to limit power consumption if the watchdog timer or real time clock is used. A suitable balun filter is the Johanson 1.6 mm × 0.8 mm × 0.7 mm 2450BM14E0003 which is matched to the nRF51422-QFAA QFN package (Johanson

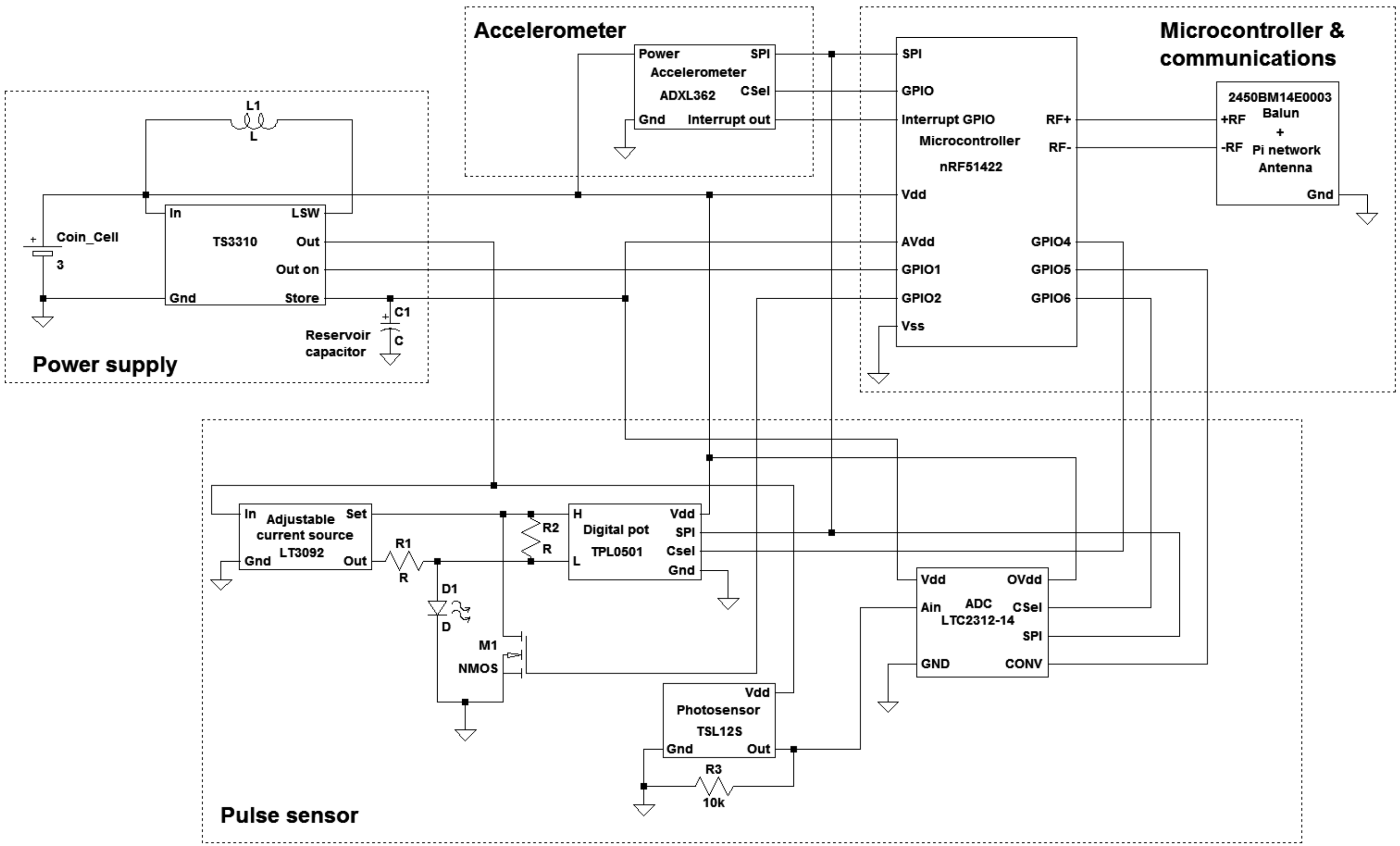


Figure C-1: Simplified fall detector system

Technology Inc., 2015), which could be used with a 2450AT18B100 chip antenna. To maximise range the antenna should be tuned to the balun by a π-network of two capacitors and a chip inductor. An alternative to a chip antenna might be an antenna wire wrapped around the fall detector.

Whilst the digital portion of the microprocessor can run directly from coin cell, the RF subsystem must use a reservoir capacitor since the coin cell is unable to supply sufficient power.

C.2 Accelerometer

The accelerometer provides the normal fall detector functionality and many devices are available which can generate an interrupt to wake-up the microcontroller when acceleration thresholds are exceeded. It can therefore wake the microprocessor when the start of a possible fall is detected, or if power permits, wake the microprocessor when almost any movement is detected. The ADXL362 accelerometer operates on 1.6 V to 3.3 V, and provides a SPI interface in a 3.3 mm $\times$ 3.3 mm $\times$ 1.14 mm package. It draws 270 nA in motion activated wake-up mode where it will generate an interrupt when acceleration rises above or falls below a threshold on each axis (Analog Devices, 2012). In active mode it consumes 3.3 µA to 4.5 µA in low noise mode at 100 samples per second.

The accelerometer's power consumption is sufficiently low for it to be powered from the coin cell to avoid the losses of the supercapacitor circuit. The pulse sensor would not be activated until at least impact had been detected by the accelerometer, and there might be a further delay to allow physiological responses to function. During pulse sensor activation the accelerometer might still be read out slowly, perhaps at 50 ms to monitor movement.

C.3 Pulse sensor

The major obstacle with the outline design is the power consumption of the pulse sensor. In the experimental studies there was no need to severely restrict power consumption but the LED alone consumed several mA, an order of magnitude more than a coin cell is rated for. The LED had a total radiant power output of about 0.19 mW with a 470 Ω current limiting resistor, as measured with a Thor Labs S401C thermal power sensor. However, the output was very directional with most of the power within a few degrees of the axis, and for this reason the photosensor was mounted very close to the LED.

With the 5 V power supply and a 3.1 V forward voltage the 470 Ω resistor would limit the current to about 3.6 mA. Skin reflectance is about 5% of incident (Anderson and Parrish, 1981), and from observation this radiant power was distributed over roughly 1 cm^2 of skin surface.

Hence a 0.2 mW cm^{-2} incident irradiance will result in a 10 µW cm^{-2} reflected irradiance, and a sensor capable of responding to a few µW cm^{-2} is needed.

The LED power might be increased easily to increase the irradiance to perhaps 0.5 mW cm^{-2}. This corresponds to a current through the LED of about 10 mA, although ideally a more focused LED would be used instead. This would provide a response from the skin of 25 µW cm^{-2}.

An optical sensor such as an AMS TSL12T (AMS AG, 2007), containing a photodiode and a transconductance amplifier, may be suitable. The 25 µW cm^{-2} irradiance will generate 2 V from the photosensor with a 5 V supply, and hence about 1.3 V with a 3.3 V supply. It produces 96 mV µW^{-2} at 5 V supply with a 10 kΩ resistor, so 63 mV µW^{-2} at 3.3 V. It is slightly less sensitive to light at shorter wavelengths, from the datasheet, it produces about 5% lower voltage at 515 nm than at 640 nm, which can be discounted for these estimates.

If the incident irradiance is raised to 0.8 mW cm^{-2}, giving 40 µW cm^{-2} reflected irradiance, then the output from the sensor will be about one volt higher, 2.3 V. One part in 11000 of 40 µW is 3.6 nW, which will produce 0.23 mV output from the photosensor. The output from the device might be improved through optimisation of the illumination level to maximise the sensitivity as discussed in Section 4.10.1. A 14 bit ADC will provide an LSB of 0.2 mV if it has a range of 0 V to 3.3 V, which is borderline since the quantisation error alone is half of this and there are other sources of error. However, if the input voltage range is reduced then the resolution improves, for example an LTC2312-14 ADC has a range provided by an internal voltage reference of 0 V to 2.5 V, producing an LSB of 0.15 mV which is just about acceptable.

The TLS12T takes 20 µs to reliably reach 90% of the new value following a large increase in light intensity. In practice settling time may be as much as ten times this, about 200 µs, for a precise measurement. The LED and sensor then needs to remain active during the ADC sampling. The LED brightness will need adjusting. If the microcontroller had a DAC then this might be done using a voltage controlled current source, but it does not so this might be done using a Linear Technology LT3092 adjustable current source driven (Linear Technology, Inc, 2014) by a digital potentiometer such as a Texas Instruments TPL0501-100 (Texas Instruments, Inc, 2011).

A resistor is provided in parallel with the digital potentiometer to avoid programming errors setting a current high enough to destroy the LED. In addition, a MOSFET shorting the SET pin to ground provides fine control of the LED timing. Since the SET pin is connected to the non-inverting side of the internal error amplifier, the amplifier will be turned off when the SET pin is pulled down to 0 V.

To carry out one pulse measurement, including the CPU idle time between readings, will require roughly 8 µC, which is the amount of charge delivered by the battery at its maximum discharge rate in $1/20$ s. A small reservoir capacitor would be required but if pulse measurements are done every 0.1 s but there is no requirement for a large reservoir as a consequence of the pulse measurements provided the other circuitry can be constrained to 0.12 mA maximum. The device would need to exclude all high frequency ambient light flicker and mains noise to operate at such a low sample rate.

Ideally some pre-fall information would be provided, although it may be be difficult with the coin cell capacity to continuously monitor the pulse.

C.4 Power supply

If a conventional manganese dioxide lithium coin cell is used, then a battery of at least 2 cm diameter is needed to support a 200 µA continuous load. A Panasonic manganese dioxide/lithium CR2412 provides 100 mA h (to 2 V) in a nominally 24.5 mm diameter, 1.2 mm thick package (Panasonic, 2005, page 51). This is not a standard IEC 60086 type but the maximum thickness in the Panasonic specifications is 1.24 mm. Whilst rated for 200 µA continuous load the specification shows the battery capable of delivering currents up to 1 mA at the cost of increased equivalent series resistance and consequent reduction in voltage and capacity.

The reservoir capacitor voltage could be maintained by a device such as a Silicon Labs TS3310 (Silicon Laboratories, Inc, 2014), a 2 mm × 2 mm boost converter at 3 V. The radio link will require 20 mA to 30 mA whilst it is transmitting. The required radio power output was assumed to be high because it is hard to make meaningful estimates without a detailed understanding of the shielding provided by wearer and watch. It is therefore essential that the amount of data transmitted is kept as small as possible. The data rate is only 20 kbps. If five features of four bytes each is transmitted for each of 20 pulses, plus another 100 bytes acceleration and pulse timing information, then this is will take 0.2 s to transmit the 500 bytes. The capacitance required is given by:

$$C = I\frac{\Delta t}{\Delta V} \tag{C.1}$$

If the capacitor provides 30 mA whilst the voltage across it drops from 3 V to 1.8 V, then the capacitance required is approximately 5 mF, or 1 mF per 100 bytes. This capacitor would also provide the reservoir for the pulse sensor. The capacitor operates at 3 V, above the 2.7 V absolute maximum for single cell aluminium electrolytic capacitors.

Solid tantalum chip capacitors have voltage limits of at least 4 V, and devices of a few mF are available, for example Vishay 592D series up to 2.2 mF (Vishay Intertechnology, Inc, 2012). These are large devices on the scale of the underwatch, 14.5 mm × 7.4 mm × 1.6 mm

Event	Current/µA	Time/µs	Charge/µC
Background and idle			
32k XOSC as LFCLK	0.4	100000	0.04
Realtime counter active	0.1	100000	0.01
CPU idle until wake-up	2.6	100000	0.26
Sleep ADC	0.2	100000	0.02
Pulse measurement, every 100 ms (real time clock interrupt wakes CPU)			
Start 16 MHz XOSC oscillator	1100	400	0.44
16 MHz oscillator debounce	470	400	0.188
CPU idle until oscillator running	3.8	800	0.00304
Start CPU	400	9.6	0.00384
Wake up ADC by pulsing CONV line			
CPU for 1 µs	2400	1	0.0024
GPIO for 1 µs	0.1	1	0.0000001
Pulse CONV	1000	1	0.001
Wait 1.1 ms for ADC voltage reference to stabilise			
CPU sleep	1.2	1100	0.00132
16 MHz oscillator standby	25	1100	0.0275
ADC wake-up	3400	1100	3.74
Turn on LED and sensor and wait 200 µs			
ADC nap	2000	200	0.4
LED MOSFET on	100	200	0.02
10 mA LED on for 200 µs	10000	200	2
CPU for 200 µs	2400	200	0.48
TSL12T MOSFET on for 200 µs	100	200	0.02
TSL12T on for 200 µs	1100	200	0.22
ADC conversion and readout			
CPU for 10 µs	2400	10	0.0024
Pulse ADC CONV	1000	1	0.001
TSL12T MOSFET on	100	8	0.0008
TSL12T sensor on	1100	8	0.0088
LED MOSFET on whilst this happens	500	8	0.05
10 mA LED for 8 µs whilst this happens	10000	8	0.08
Clock 13 bytes on ADC at 4 MHz using SPI	200	4.25	0.00085
ADC power during conversion and readout	3400	6.25	0.02125
Reservoir capacitor charge used			7.7 µC
Charge recovery time at 200 µA			39 ms

Table C.1: Tentative power consumption estimate for sampling the pulse amplitude every 100 ms using 200 µs long LED/sensor activation followed by readout. Rough estimate only since signal rise times will be affected by internal capacitances and there will be other small sources of power drain. The calculation excludes the battery charging circuit, accelerometer and RF link and assumes that there is no overhead in controlling the LED current.

and several would be required, although the height might be reduced slightly by insetting into the printed circuit board.

C.5 Conclusion

With judicious design and selection of components the pulse sensor will not need a significant reservoir capacitor, but the radio link will need one of a few mF, which would be a restriction on the size of the underwatch device. However, the coin cell's 0.2 mA rated continuous current limit places serious restrictions on the pulse sensor, and if greater performance is needed from the device then a higher performance battery would be needed.

Appendix D

Ethical approvals

D.1 Chapter 3 Body position from pulse shape - a first study

```
From: "James Friedlander-Boss" <J.D.Friedlander-Boss@bath.ac.uk>
To: <J.L.Leake@bath.ac.uk>
Subject: REACH Feedback
Date: Mon, 18 Feb 2013 14:43:34 -0000

Dear Jason,
Full title of study: Is pulse shape affected by body position?
REACH reference number: EP 12/13 33
The Research Ethics Approval Committee for Health (REACH) reviewed
the amendments to the above application following its meeting held
on 13th February 2013.
On behalf of the Committee, I am pleased to confirm a favourable
ethical opinion of the above research on the basis described in
the application form and supporting documentation.
Please inform REACH about any substantial amendments made to the
study if they have ethical implications.
Kind Regards
James Friedlander-Boss
Department Co-ordinator
```

```
Date: Tue, 05 Mar 2013 10:04:02 +0000
From: Helen Lucey <H.Lucey@bath.ac.uk>
Organization: University of Bath
To: Jason Leake <J.L.Leake@bath.ac.uk>
Subject: Ethics 13-037

Dear Jason

Reference Number 13-037

The ethics committee have considered your ethics proposal for the
study entitled 'Is pulse shape affected by body position?' and
have given it full ethical approval.

Best wishes with your research.

Helen Lucey
Chair of Psychology Ethics Committee
```

D.2 Chapter 4 Body position from pulse shape - a larger study

```
Date: Fri, 13 Jun 2014 14:44:10 +0100
From: Gordon Taylor <G.J.Taylor@bath.ac.uk>
Organization: University of Bath
To: Jason Leake <jll26@bath.ac.uk>
CC: E.M.Keogh@bath.ac.uk, "N. Harris" <n.harris@bath.ac.uk>,
 C.Eccleston@bath.ac.uk, Rachael Yates <R.M.Yates@bath.ac.uk>
Subject: Re: Request to ammend EP 12/13 33

Dear Jason,

Thanks for the poster, consent and information sheets and thanks in
particular for highlighting the changes.

I am happy to approve this extension to your study.

Best wishes,

Gordon
Chair of REACH.
--
Dr Gordon Taylor
Reader in Medical Statistics
Department for Health
University of Bath
Bath, BA2 7AY
```

```
Date: Mon, 16 Jun 2014 11:38:15 +0100
From: Psychology Ethics Committee <psychology-ethics@bath.ac.uk>
To: Jason Leake <jll26@bath.ac.uk>
Subject: Re: Ethics 14-141

Hi Jason

Thank you for sending the approval from REACH. I can now confirm
that you have ethical approval to continue with your study.

Best wishes

--
Dr Helen Lucey
Chair Psychology Ethics Committee
University of Bath
```

D.3 Chapter 5 Body position from pulse shape in elderly people

```
Date: Wed, 18 Feb 2015 15:57:55 +0000
From: Rachael Yates <R.M.Yates@bath.ac.uk>
Organization: University of Bath
To: Jason Leake <J.L.Leake@bath.ac.uk>
CC: Chris Eccleston <C.Eccleston@bath.ac.uk>
Subject: REACH Feedback - Jason Leake

Dear Jason,

Full title of study: How does body position affect pulse shape in
people aged 65+?
REACH reference number: EP 14/15 115

The Research Ethics Approval Committee for Health (REACH) reviewed
the above application at its meeting held on the 12th February 2015.

On behalf of the Committee, I am pleased to confirm that the
Committee would be happy to provide a favourable ethical opinion of
the above research,(on the basis described in the application form
and supporting documentation). The Committee raised that perhaps
you should consider whether the controls of abstaining from caffeine
and alcohol for one hour prior to the study are sufficient, or
whether other drugs should be included in this.

Please inform REACH about any substantial amendments made to the
study if they have ethical implications.

Kind regards

Rachael Yates
Department Co-ordinator
```

```
Date: Sat, 07 Mar 2015 06:35:10 +0000
From: Psychology Research Ethics Committee
<psychology-ethics@bath.ac.uk>
To: Jason Leake <J.L.Leake@bath.ac.uk>
Cc: g.j.taylor@bath.ac.uk
Subject: Ethics 15-024

Dear Jason

The University Ethics Committee has confirmed that any committee
operating on its behalf (REACH, Psychology) provides approval on
behalf of the University. Therefore additional approval from an
additional committee is not required internally.

Best wishes for your research,
Dr Michael J Proulx
Chair, Psychology Research Ethics Committee
```

D.4 Chapter 6 Designing a fall detector for people with dementia

```
Date: Tue, 23 Sep 2014 17:21:58 +0100
From: Rachael Yates <R.M.Yates@bath.ac.uk>
Organization: University of Bath
To: Jason Leake <J.L.Leake@bath.ac.uk>
Subject: REACH Feedback -Jason Leake

Dear Jason,

Full title of study:Requirements for a wrist-worn fall detector for
people with dementia
REACH reference number: EP 14/15 7.

The Research Ethics Approval Committee for Health (REACH) reviewed
the above application at its meeting held on the 17th September.

On behalf of the Committee, I am pleased to confirm that the
Committee would be happy to provide a favourable ethical opinion of
the above research on the basis described in the application form
and supporting documentation.The Committeee did however, raise
concern regarding the significant number of exclusions to the study
given that a user centered design approach is employed. Whilst the
committee is not withholding approval on this point they recommend
that you give this some consideration.

Please inform REACH about any substantial amendments made to the
study if they have ethical implications.

Kind regards

Rachael Yates
Department Co-ordinator
```

```
Date: Fri, 17 Oct 2014 11:40:13 +0100
From: mjp51@bath.ac.uk
To: Jason Leake <J.L.Leake@bath.ac.uk>
Cc: Edmund Keogh <E.M.Keogh@bath.ac.uk>
Subject: Ethics 14-202

Dear Jason Leake

Reference Number 14-202

The ethics committee have considered your ethics proposal for the
study entitled "Requirements for a wrist-worn fall detector for
people with demetia" and have given it full ethical approval by
Chair's Action.

Best wishes with your research.

Dr Michael J Proulx
Chair of Psychology Ethics Committee
```

D.5 Chapter 7 The underwatch fall detector concept

```
Date: Mon, 19 Jan 2015 16:20:09 +0000
From: Rachael Yates <R.M.Yates@bath.ac.uk>
Organization: University of Bath
To: Jason Leake <J.L.Leake@bath.ac.uk>
Subject: REACH Feedback - Jason Leake (updated)

Dear Jason,

Full title of study:Evaluation of the physical characteristics of
wrist-worn detectors for people with dementia.
REACH reference number: EP 14/15 98.

The Research Ethics Approval Committee for Health (REACH) reviewed
the the above application at its meeting held on the 14th January
2015.

On behalf of the Committee, I am pleased to confirm that the
Committee would be happy to provide a favourable ethical opinion of
the above research,(on the basis described in the application form
and supporting documentation).

Please inform REACH about any substantial amendments made to the
study if they have ethical implications.

Kind regards

Rachael Yates
Department Co-ordinator
```

```
Date: Fri, 06 Feb 2015 08:39:00 +0000
From: Psychology Research Ethics Committee
<psychology-ethics@bath.ac.uk>
To: Jason Leake <J.L.Leake@bath.ac.uk>
Subject: Ethics 15-004

Dear Jason Leake

Reference Number 15-004 Evaluation of the physical characteristics
of wrist-worn fall detectors for people with dementia.

The ethics committee have considered your ethics proposal for the
study above and have given it full ethical approval.

Best wishes with your research,
Dr Michael J Proulx
Chair, Psychology Research Ethics Committee
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